Global competition dynamics of fossil fuels and renewable energy under climate policies and peak oil: A behavioural model

Paolo Zeppini[a,b*]

Jeroen C.J.M. van den Bergh[c,d,e]

[a] *Department of Economics, University of Bath, UK*

[b] *Université Côte d'Azur, CNRS, GREDEG, France*

[c] *ICREA, Barcelona, Spain*

[d] *Institute of Environmental Science and Technology, Universitat Autònoma de Barcelona, Spain*

[e] *School of Business and Economics & Institute for Environmental Studies, VU University Amsterdam, The Netherlands*

Abstract

We develop a stochastic decision model to analyse the global competitive dynamics of fossil fuels and renewable energy. It describes *coal*, *oil/gas*, *solar* and *wind*. These differ not only in pollution intensities but also in profitability and innovation potential. The model accounts for the effect of learning curves, path-dependence and climate policies. Adoption shares endogenously affect agents' utility through increasing returns to adoption, learning, and a 'peak oil' capacity constraint. We find that peak oil induces a transition to *coal* rather than renewable energy, which worsens climate change. By introducing climate policies - such as a carbon tax, market adoption or *R&D* subsidies for renewables, and eliminating existing subsidies for fossil fuels - we identify potential transition patterns to a low-carbon energy system. Model analysis clarifies two main features of climate policies: which ones solve the climate problem, i.e. do not surpass the critical carbon budget; and how uncertain or variable are final market shares of energy sources.

Key words: climate change, energy policy, externalities, learning, peak oil.

*Corresponding author. Email: paolo.zeppini@gmail.com.

1 Introduction

To solve climate change our energy system needs to alter drastically. At present, fossil fuels, such as coal and natural gas, dominate energy supply for power generation as well as transport systems, being responsible for about three quarters of all anthropogenic CO_2 emissions (IPCC, 2014). While renewable energy, notably in the form of solar and wind electricity, is growing relatively fast, it still has a small share in overall supply. We study the transition from fossil fuels to low-carbon energy sources by modelling the global competitive dynamics of both types of energy sources, taking into account increasing returns causing path-dependence, learning curves, and climate policy interventions.

Relevant energy policies include a carbon tax, market subsidies, and *R&D* subsidies. A carbon tax increases the cost of generating power with fossil fuels or using fossil fuel vehicles. Market subsidies promote adoption of renewable energy. *R&D* subsidies stimulate innovation and the learning curve of renewable energy. Our aim is to assess the effectiveness of various combinations of these policies in terms of emissions reduction.

To achieve this aim, we develop a formal model describing four different energy sources which compete in a global market, namely *coal*, *gas/oil*, *solar* and *wind*. We focus on these four for the following reasons: they are important either now or, likely, in the near future; they include two types of fossil fuels that have distinct carbon intensities; and they cover two types of renewable energy sources characterized by distinct costs and learning rates. The resulting structure allows addressing the main issues involved in analysing a shift away from fossil fuels to renewable energy, such as in which order fossil fuels will be phased out, or which renewable alternative is likely to diffuse or merits more policy support. Gas and oil are combined for simplicity, given that they are partly substitutes. We discard nuclear and hydropower sources, as they have been rather stable and do not show directed dynamics during the last five decades. Our model can be considered to implicitly describe electricity and transport systems, the main users of fossil fuels. Indeed, a transition to renewable electricity will likely involve a 'sub-transition' to power plants using renewable energy together with a 'sub-transition' in mobility and transport to electric cars.

In our model the four technologies for power generation are available for adoption to a large pool of agents, who make decisions sequentially, one at each time period. Decisions are based on three factors: intrinsic profitability, increasing returns to scale and learning. Agents include both producers, notably of electricity, and consumers, especially in their role of users of transport fuels. The model addresses a long-run competition dynamics of energy sources, treating them as perfect substitutes. While in the short term perfect substitutability is unrealistic, in the long run it is a reasonable assumption, because of market shake-out of non-profitable activities, capital replacement and technological innovation.

The presence of positive externalities due to increasing returns to adoption, scale economies and infrastructure complementarities causes a certain technology to be more appealing the more it is adopted. This setting represents the basic scenario of technology competition with positive externalities as originally modelled by Arthur (1989). An extension of this model to environmental economics was developed in Zeppini and van den Bergh (2011). Building on this framework, we introduce here a learning curve for *solar* and *wind* energy, representing endogenous technological progress, adding a scheme of *R&D* subsidies and market subsidies for facilitating adoption. Moreover, we introduce a tax on CO_2 emissions. On top of this we model the impact of peak oil dynamics, meaning an event where *oil* and *gas* subsequently become very scarce causing their prices to sharply increase (Chapman, 2014). Finally, we also look at the impact of removing current subsidies on fossil fuels (Coady et al., 2015).

Our model is positioned in between broader models of transitions and diffusion or multi-phase process models (Safarzyńska et al., 2012). More than predictive, it is intended for analysing policy effectiveness, in terms of staying in the carbon budget. The model generates transitory dynamics before an equilibrium state is attained. This allows to identify short-term, medium-term and long-term effects of policy interventions, including which climate policy packages are able to avoid surpassing the 2^oC target.

The remainder of the paper is organised as follows. Section 2 describes the model in general terms. Section 3 sets parameters in accordance with insights from the literature about the critical carbon budget and data about the energy sector. Section 4 presents scenario settings and related simulations results. A summary of the scenarios, policies and findings can be found in Table 1. Section 5 concludes.

2 The Model

A vector with market shares of the different energy sources describes the competition dynamics, namely $\mathbf{x} = (x_c, x_o, x_s, x_w)$ for *coal, oil/gas, solar* and *wind.* The sequential decision process is modelled with an urn scheme, where at each time step the probability distribution of $\mathbf{x}$ depends on all previous decisions. Following Arthur et al. (1987), the vector of market shares changes according to the difference equation

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \frac{1}{w+t}[\alpha(\mathbf{x_t}) - \mathbf{x_t}], \tag{1}$$

where $\alpha(\mathbf{x}_t)$ is a binomial 4-dimensional variable associated with the four technological options, expressing the decision by an agent at time t. The parameter w can be considered to represent the historical number of decisions, before $t = 0$. More practically, it serves to scale forward the timing of the stochastic process.

Eq. (1) represents a *Polya process*, a type of Markov process that responds to the idea of urn extraction schemes (Arthur et al., 1987). The equation describing competition dynamics (1) changes with time t, which makes the decision environment time dependent. The binomial variable $\alpha(\mathbf{x}_t) = (\alpha_s, \alpha_w, \alpha_o, \alpha_c)$ is defined as follows:

$$\alpha_{a,t}(\mathbf{x}_t) = \begin{cases} 1 & \text{with probability } q_a(\mathbf{x}_t) \\ 0 & \text{with probability } 1 - q_a(\mathbf{x}_t), \end{cases} \tag{2}$$

with $a = c, o, s, w$ for *coal, oil/gas, solar, wind.* The probability q_a depends on the state variable $\mathbf{x}_t$, which is an endogenous factor in the sequential decision system: the distribution $q_a(\mathbf{x}_t)$ feeds back into the difference equation (1), and dictates the value of $\mathbf{x}_{t+1}$. In order to capture the multiple equilibria of the technology adoption process and the consequent lock-in effect, a stylised fact of technology competition, we adopt a logistic probability function. This functional specification links to the probabilistic distributions of discrete choice theory (McFadden, 1981), especially when this distribution is used as a revision protocol in behavioural models of non-linear economic dynamics (Hommes, 2013). For technology $a \in A = \{coal, oil/gas, solar, wind\}$ we then write:

$$q_a(\mathbf{x}_t) = \frac{e^{\beta u_a(x_{a,1},\ldots,x_{a,t})}}{\sum_{b\in A} e^{\beta u_b(x_{b,1},\ldots,x_{b,t})}}. \tag{3}$$

The function $u_a(x_{a,1}, \ldots, x_{a,t})$ expresses the utility - or profitability - of choosing technology a, with $a = c, o, s, w$ for *coal, oil/gas, solar* and *wind.* Its value depends on the share of users of a technology, in a way that will be specified shortly. Our model is then connected to discrete choice models with evolutionary dynamics and switching behaviour (Hommes, 2006) and, in particular Zeppini (2015) for the presence of proportional spillovers. The difference with our model is the probabilistic factor (2), which makes the state variable (1) of our model a stochastic process. This is an important feature that distinguishes our sequential decision model from deterministic synchronous decision models with switching behaviour like Brock and Hommes (1997) and Zeppini (2015). In a synchronous model, all agents make a decision at the same time t, and decisions are repeated at each successive time, in an updated environment. In a sequential decision model like ours, only one agent makes a decision at a given time t, and this decision is once and for all. The decision environment is updated here as well, but never repeats itself over successive decisions.[1]

The sequential decisions framework is more suitable for the energy sector than a synchronous framework, as decisions of this sort are infrequent. To illustrate this for consumers, their decision relates not only to everyday use of transportation options, but also to the purchase of vehicles, and thus the type of energy used. Moreover, comparing to synchronous models, sequential decision models allow studying in more detail the transitory process before convergence to a long-run attractor. Sequential decision settings further

[1]The system (1) is *non-autonomous*, or *non-time-invariant*.

describe better path-dependent mechanisms due to increasing returns on adoption, which is an important feature of the energy sector.

For a large population of decision makers, the probability of an agent adopting a choice option coincides with the fraction of agents making that choice. Since the market share $\mathbf{x}_t$ is the state variable of utility functions, the long run value of market shares is a fixed point $\mathbf{x} = q_a(\mathbf{x})$ of the probability (3). The parameter β has two interpretations: it can measure preferences shocks, i.e. the heterogeneity of adopters' preferences, as in McFadden (1981); or it can measure bounded rationality, the fact that adopters make small mistakes in evaluating utility u_a, as in Brock and Hommes (1997). In both interpretations a noise term is added to the deterministic utility u_a, and β is inversely proportional to the variance of this noise. In a large population of decision-makers the probability q_a approaches a logistic function: the larger β, the more q_a has a step-like shape. The lower β, the smoother q_a (see Figure 1 for an illustrative example). The crucial aspect in this

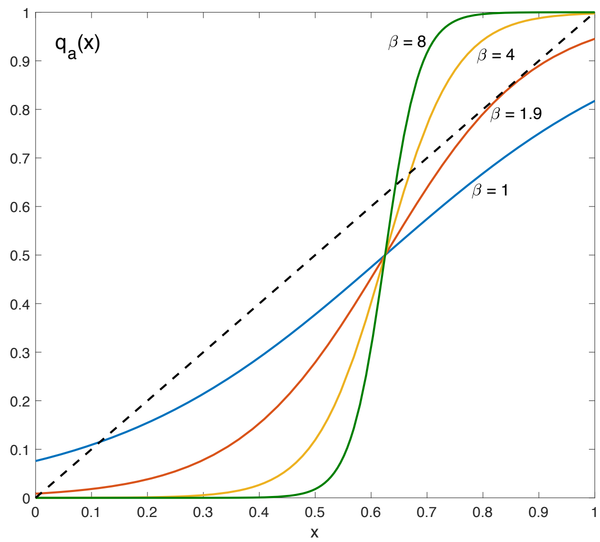

Figure 1: Examples of logistic probability distribution for different values of the parameter β, in a 1-dimensional case. For $\beta = 1$ there is only one equilibrium (fixed point); for $\beta \simeq 1.9$ another equilibrium appears (two fixed points). For $\beta = 4$ and $\beta = 8$ there are two stable equilibria and one unstable equilibrium in between.

probabilistic decision process is that when β is large enough, there are two fixed points and then two stable attractors for the probability of a given choice option 3, and then for energy source. This is how we model path dependence and technological lock-in. In the example of Figure 1 there are two attractors for $\beta = 4$ and $\beta = 8$.

Climate policy is implemented in our model through four channels: a carbon tax, market subsidies to stimulate adoption of renewable energy, *R&D* subsidies for renewables, and removal of existing fossil fuel subsidies. We assume that only fossil fuels emit CO_2, since indirect emissions from *solar* and *wind* energy are relatively small. Learning only applies to renewables, which reflects that *coal* and *oil/gas* are mature technologies. This is justified by empirical evidence from learning curves over the last 30 years (Farmer and Trancik, 2007). All these factors are captured in our model through appropriate terms in the utility function of decision makers, which read as follows:

$$u_c(x_{c,t}) = u_{c,0} + \rho(1 + \sigma_c^M)x_{c,t} - \upsilon\tau e_c, \tag{4}$$

$$u_o(x_{o,t}) = u_{o,0} + \rho(1 + \sigma_o^M)x_{o,t} - \upsilon\tau e_o - pX_{o,t}, \tag{5}$$

$$u_s(x_{s,t}) = u_{s,0} + \rho(1 + \sigma_s^M)x_{s,t} - \frac{(X_{s,t})^{-L_s}}{(1 + \sigma_s^R)}, \tag{6}$$

$$u_w(x_{w,t}) = u_{w,0} + \rho(1 + \sigma_w^M)x_{w,t} - \frac{(X_{w,t})^{-L_w}}{(1 + \sigma_w^R)}. \tag{7}$$

The first constant term in each utility specification is directly linked to the initial or intrinsic profitability of a technology at time $t = 0$. This term is used to calibrate the model empirically and for different policy scenarios.

The second term expresses a positive feedback due to increasing returns to adoption (Arthur, 1989), stemming from economies of scale, complementary technologies, infrastructure effects or demand side effects like network externalities (Katz and Shapiro, 1985). The larger the parameter $\rho > 0$, the stronger increasing returns. This utility term can also describe social influence, as in discrete choice models with social interactions (Brock and Durlauf, 2001). It serves as a channel for policy impacts. In particular, *market subsidies* $\sigma^M > 0$ enhance the intensity of increasing returns associated with renewable energy, by raising the marginal utility of a new adoption. The parameters σ_c^M and σ_o^M denote current subsidies for fossil fuels, which might be removed as part of environmental policy intervention as they contribute to excessive emissions. In addition, σ_s^M and σ_w^M are market subsidies to encourage adoption of renewables. The model is used to examine the relative effect of these different policy actions, or a combination therefore.

As a basic instrument of climate policy we consider a tax τ on CO_2 emissions in the third term of the utility for *oil/gas* and *coal*. This is equivalent to a carbon tax on fuels as emissions generated by a particular fuel are proportional to its carbon content. Since emission intensities e_o and e_c (for *oil/gas* and *coal*, respectively) are expressed in terms of $Gt(CO_2)/TJ$, the emission tax units are \$ per tonne of CO_2 emitted, with a conversion factor υ measured in TJ, so as to have utility terms measured in monetary units.

The variables in capital letters express cumulative quantities that sum up market shares over time up to a date t, with $X_{o,t} = \sum_{r=1}^{t} x_{o,r}$ for *gas/oil*, $X_{s,t} = \sum_{r=1}^{t} x_{s,r}$ for *solar*, and $X_{w,t} = \sum_{r=1}^{t} x_{w,r}$ for *wind*. For *gas/oil* we consider a *peak* effect through the last term of Eq. (5). Since 2000, *oil* prices have been on the rise most of the time, reaching above 140\$ per barrel. Prices underwent corrections during the recent economic crisis and in 2014, but since then have started to recover steadily, and are above 70\$ per barrel currently.

Another indicator of an imminent peak oil era is the advent of unconventional fossil fuels, such as oil sands and shale gas. There is continuing debate on the importance of peak oil, as well as how to address it in formal modelling (Holland, 2008; Holland et al., 2013). In this study, we model peak oil by letting the utility of *oil/gas* be negatively affected by the energy price through a term that includes the sum of *oil/gas* market shares at each time step. This effect is regulated through a 'peak' coefficient $p > 0$. According to the economic theory of exhaustible resources (Dasgupta and Heal, 1979), under increasing scarcity the resource price presents a reaction curve of progressive (say quadratic) increase towards the price of the backstop technology (in this case, depending on the scenario and time, *coal*, *solar* or *wind*). The peak oil term in the utility of *oil/gas* is linear in cumulated shares, and approximates a quadratic reaction curve through integration.[2]

The utility of renewables (Equations 6 and 7) presents a more complex term describing a learning curve. There is empirical evidence that because of technological progress production costs go down depending on cumulative experience, hence the learning curve is often referred to as an "experience curve". In particular, the unit production cost depends on cumulative experience following a negative exponential law, with cumulative experience expressed here by summing market shares over time. This is captured in our model by the last term of utility for *solar* and *wind*, which can be read as a cost paid for energy production. This cost decreases with overall adoptions of each renewable energy source. We calibrate this term using learning rates L_s and L_w from empirical studies of learning in the energy sector (Rubin et al., 2015), with $L_s = 20\%$ and $L_w = 10\%$.

Learning is positively affected by *R&D* subsidies $\sigma^R > 0$, which are an element of climate policy. These influence the cost of energy production in a proportional way, i.e. not through the learning rate. The precise interpretation of this is not easy as the learning curve reflects the joint cumulative and synergetic effects of scale, experience, learning-by-doing and innovation. Subsidies can be seen to magnify the innovation contribution to these effects. As the learning speed is captured by the exponent, informed by empirical studies, we decided to not let the subsidies affect this parameter but the entire term.

R&D subsidies are financed by revenues from the emission tax, a mechanism that is described in our model by the following specification: the subsidies allocated in period t to each of the two renewables in order to boost their learning are

$$\begin{aligned} \sigma^R_{s,t} &= \gamma\tau(e_c x_{c,t} + e_o x_{o,t}), \\ \sigma^R_{w,t} &= (1-\gamma)\tau(e_c x_{c,t} + e_o x_{o,t}), \end{aligned} \tag{8}$$

[2]We do not consider a peak coal factor in our model for a number of reasons: first, peak coal is debated and much further in time, hence not very relevant. Moreover, adding a second, later peak effect does not add much to model conceptually. Finally, an undesirable transition to coal is one possible outcome of peak oil, and this result would be less clear with a peak coal effect.

where γ is the allocation fraction. The motivation for this approach is twofold. First, it makes sense to use tax revenues for subsidies within an environmental policy package, rather than financing subsidies out of the general government budget. This choice can make both tax and subsidies more palatable to the general public. Second, a carbon tax would select for cost-effective technologies, while promising but still expensive options would be selected out. To overcome this shortcoming, a complementary public support of $R\&D$, as in the form of subsidies, is required to keep such technological options open. The higher the carbon tax, the stronger such support needs to be. Hence, a proportionality as assumed in equation (8) makes sense. In the analysis of Section 4 we consider a fixed and a dynamic allocation factor γ. In the dynamic allocation at each time γ is set equal to the relative proportion of the two renewables' market shares.

We assume that fossil fuels do not experience significant learning as they are associated with mature extraction and combustion technologies. The long-run attractors for the dynamic system (1) are fixed points of the function q_a in Eq. (3):[3]

Proposition 1 *The process* $\mathbf{x}_t$ *converges over time to a limit value* $\mathbf{x}^* = q_a(\mathbf{x}^*)$ *for* $a \in A = \{coal, gas/oil, solar, wind\}$.

Intuitively, for a fixed point $\mathbf{x}^*$ the binomial variable (2) becomes

$$\alpha_{a,t}(\mathbf{x}^*) = \begin{cases} 1 & \text{with probability } \mathbf{x}^* \\ \\ 0 & \text{with probability } 1 - \mathbf{x}^*, \end{cases} \tag{9}$$

and its expected value is exactly $\mathbf{x}^*$. This is why in the long run the difference in the second hand side of (1) vanishes, and $\mathbf{x}_t \to \mathbf{x}^*$.

The formal proof of convergence is provided in Arthur et al. (1987). The associated "long run value" is the counterpart of a stable steady state in the deterministic dynamic discrete choice models of Hommes (2006), the difference being the stochastic nature of our model, that is due to the random urn scheme.

Proposition 2 *If* $\beta \to \infty$ *only the corner solutions* $(1, 0, 0, 0)$*,* $(0, 1, 0, 0)$*,* $(0, 0, 1, 0)$ *and* $(0, 0, 0, 1)$ *can be equilibria of the system.*

Such corner solutions are realised whenever one technology a has a higher profitability than the others, or $u_a > u_b$ for any $b \neq a$. The equal allocation equilibrium only occurs in the case of equally profitable technologies, or $u_a = u_b$ for any a, b. The equal allocation is the only outcome in the opposite limit of the intensity of choice β:

Proposition 3 *If* $\beta \to 0$ *only the vector* $\left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}\right)$ *is an equilibrium of the system.*

[3]The value of $\mathbf{x}$ that makes utility levels (4 - 7) equal, the indifference point, is not a long run equilibrium in general, as we explain in Appendix A.

Finite values of β give long run attractors that are different from the corner solutions and the symmetric vector. However, the functional specification of the allocation function (3) is characterised by a S=shape with fixed points that are very close to the corner solutions already for values of β of few units. In Appendix C we undertake an extensive sensitivity analysis of this and of the other parameters of the model.

3 Empirical Application

Analytical solutions of our model are impossible to obtain with finite values of β. More than the value of the long run equilibrium, what counts for the issue of sustainability is the transitory dynamics through which this equilibrium is attained, which may encompass decades. The competition dynamics before the attainment of the equilibrium drives the amount of CO_2 emitted and accumulated in the atmosphere, and then it is the real mechanism that may or may not limit the rise in global temperatures below a desired level, as 2^oC for instance. For all these reasons, we run an extensive numerical analysis of the model in various scenarios. And to make the results empirically sound, we calibrate the model on the most recent estimation of relevant parameters such as the emission intensity of fossil fuels and the actual market shares of the four energy sources.

In line with the 2015 Paris agreement on climate change, a global climate policy aims to stay within a *carbon budget*, defined as the maximum $\mathrm{CO_2}$ emissions to the atmosphere allowed in order to keep global warming below 2^oC. While there is a range of estimates of this budget (Rogelj et al., 2016; Peters, 2018), we adopt a recent estimate, which is around 790 Gtonnes of $\mathrm{CO_2}$ over the period 2015 - 2050, in line with earlier studies to which our results can be compared (King and van den Bergh, 2018; OECD and IEA, 2017).

The total stock of carbon E accumulated over a time horizon t is obtained by aggregating emissions in the time interval $[0, t]$. We compare the carbon budget for 2^oC with aggregated emission expressed as follows:

$$E_t \equiv \sum_{r=1}^{t} c(r)\big(e_c x_{c,r} + e_o x_{o,r}\big) \tag{10}$$

where $c(r)$ is total energy consumption in time period r. The competition dynamics of energy sources described by our model takes place within the overall context of an absolute energy consumption trend $c(r)$. Figure 2 gives an account of the time series of global energy consumption during the last five decades.

The linear trend that characterises global consumption dynamics is captured by an exogenous function $g_t = g_0(1 + kt)$. Over the last five decades consumption has tripled over the time period $\Delta t = 50$ years from 1965 until 2015 (Figure 2). Accordingly, we set $1 + k\Delta t = 3$. We select a time horizon of 35 years for our study. A reasonable

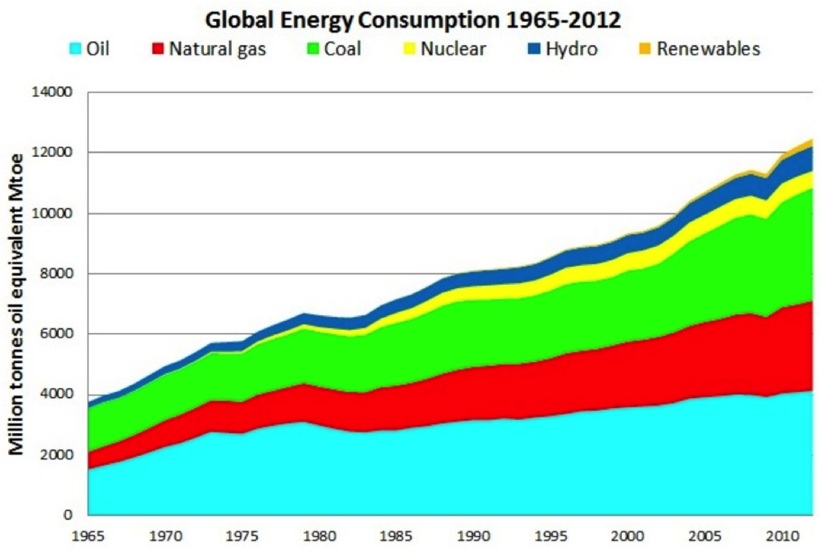

Figure 2: Global energy use (BP Statistical Review of World Energy, 2015).

assumption for the time scale of our sequential decision model is then one day. The time horizon translates into 12775 days, then. Since there are 18250 days in 50 years, we obtain $k = 2/18250 \cdot day^{-1}$. The initial time of our simulations is 2015, when consumption was about 14300 $MTOE$ (MegaTonnes of Oil Equivalent), or 600 EJ (ExaJoule).[4] This means an estimated daily consumption equal to $g_0 = 14300/365 \simeq 39$ $MTOE/day$, or 1.6 EJ/day.

In order to use the price of carbon for the emission tax rate τ, we set $v = 10^{-4}TJ$ as value for the conversion factor that makes the utility terms in (4) and (5) comparable. We will consider a low and high value of this tax, since there is much debate on this point. As a low value we take the U.S. EPA estimate of the social cost of carbon which equals $33\$/tCO_2$.[5] As a high value we use a meta-estimate based on the literature, equal to $125\$/tCO_2$ (van den Bergh and Botzen, 2014). This range is compatible with the range $40 - 100\$/tCO_2$ proposed by Stern and Stiglitz (2017).

We use data from the International Energy Agency for the initial conditions of market shares. After taking out nuclear power, hydropower and biofuels in power generation, and normalising for the four energy sources that are the focus of our inquiry, we have that *coal* accounts for 33% of energy production, *oil/gas* for 55%, *solar* for 3%, and *wind* for 9%.[6] Pollution intensities are $e_c = 9.7 \cdot 10^{-5} Mt(CO_2)/TJ$ for *coal* and $e_o = 6.97 \cdot 10^{-5} Mt(CO_2)/TJ$ for *oil/gas*. The latter is obtained as a weighted average of

[4] 1 Tonne Oil Equivalent $\simeq$ 42 GigaJoule energy. MegaTonnes = 10^6 tonnes, ExaJoule = 10^{18} Joules.

[5] Interagency Working Group on Social Cost of Carbon, Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis under Executive Order 12866 (US Government, 2013).

[6] The actual shares of the global market in 2015 are 29% for *coal*, 31% for *oil* and 21% for *gas* (IEA Key World Energy Statistics). In particular, the market shares of *coal* and *oil/gas* is equal to 37.5% and 62.5%, respectively.

emission intensities of oil ($7.95 \cdot 10^{-5} Mt(CO_2)/TJ$) and gas ($5.9 \cdot 10^{-5} Mt(CO_2)/TJ$), based on their share in global primary energy supply (King and van den Bergh, 2018). The market shares 33% and 55% of *coal* and *oil/gas* correspond to relative proportions 37.5% and 62.5%, respectively, from which daily CO_2 emissions in 2015 can be calculated:

$$e_0 \sim 1.6 EJ/day \cdot (0.625 \cdot 6.97 + 0.375 \cdot 9.7) \cdot 10^{-5} Mt(CO_2)/TJ \simeq 128 \frac{Mt(CO_2)}{day}.$$

If energy consumption would stop growing and emissions remained at the actual level, we would exhaust the carbon budget in $790Gt/128Mt/day \simeq 6172$ days, about $\simeq 17$ years. Because of consumption growth, this time is going to be considerably shorter in a business as usual (BAU) scenario. The introduction of climate policies makes this time longer, and possibly the carbon budget is never reached. But results strongly depend on the competition dynamics of energy sources. This is exactly the main focus of our study.

For the intensity of choice we use $\beta = 4$, for positive externalities we set $\rho = 2$ and for the peak oil parameter we set $p = 0.0005$. Our model is quite robust with respect to the choice of these parameters. In Appendix C we do a sensitivity analysis, which motivates our choice of values.[7]

4 Numerical Simulations

4.1 Policy scenario settings

We use our model to simulate market shares and carbon emissions over the period 2015 - 2050, and compare the latter to the carbon budget associated to a 2^oC temperature increase. In our numerical simulations we run the model 10 times for a given setting of parameters value, in order to properly evaluate the variability of results from the stochastic process underlying the sequential decision model.

Different policy scenarios are defined by making use of the various components in the utility of energy sources (Equations 4-7). In setting the scenarios of our policy analysis we have considered the main themes of the motivation for our study, explained in Section 3. First, the enduring debate on the cost-effectiveness of renewable energy in comparison

[7] We find that while β only reduces the variability of simulated choices, ρ also affects the competition dynamics but only between the two fossil fuels. Emission are little influenced by ρ. This fact implies that to delay or avoid cumulated emissions reaching the carbon budget we need a transition to renewables. Regarding the peak oil utility term, the time width of *oil* dominance in terms of time shares becomes smaller with an increasing value of the parameter p, as expected. However, the time when the carbon budget is exhausted scales down at a decreasing speed. This means that similarly to ρ, also p has an impact on the transitory competition dynamics of energy sources, but an increasingly limited impact on the time when the carbon budget is exhausted.

with fossil fuels, as, among others, reflected by the uncertainty ranges of the energy return on (energy) investment (EROI) (King and van den Bergh, 2018). Second, the debate on existing fossil fuel subsidies (Coady et al., 2015). Third, the implementation of various types of climate policy (Baranzini et al., 2017). The details of the different scenarios are as follows:

(I) ***Business as Usual (BAU)***. The first scenario approximates the baseline situation without policy and with fossil fuels being more profitable than renewables. In Equations (4-7) we set $\sigma_s^M = \sigma_w^M = \sigma_c^M = \sigma_o^M = 0$ (no market subsidies), $\tau = 0$ (no emission tax and no $R\&D$ subsidies), and $u_{c,0} = u_{o,0} = u_{w,0} = u_{s,0} = 0$, which gives an ordering of initial utility levels $u_o(t=0) > u_c(t=0) > u_w(t=0) > u_s(t=0)$ (provided that p is small enough). This setting of distinct initial profitability of energy sources approximates the actual situation. The ordering is guaranteed provided the peak-oil effect is small at $t = 0$, which is the case since $\rho(x_{o,0} - x_{c,0}) >> px_{o,0}$, or $p << \rho\big(1 - \frac{x_{c,0}}{x_{o,0}}\big)$. As $\rho = 2$, and actual market shares are $x_{o,0} = 0.55$ and $x_{c,0} = 0.33$, the condition $p << 0.8$ needs to hold. We set the value $p = 0.0005$.

(II) ***Silver bullet: a major technological breakthrough***. Here renewable resources are assumed to be equally profitable as fossil fuels at the start of the simulation, due to a hypothetical technological breakthrough. In formal terms, this gives $u_o(t = 0) = u_c(t = 0) = u_w(t = 0) = u_s(t = 0) = u_0$. We take *coal* as the reference, and set $u_{c,0} = 0$. Given that $x_{c,0} = 0.33$, we obtain the starting utility level $u_0 = \rho \times x_{c,0} = 2 \times 0.33 = 0.66$. For gas/oil we have $u_o(t = 0) = u_{o,0} + \rho x_{o,0} - px_{o,0} = u_{o,0} + (2 - 0.0005) \times 0.55 = u_{o,0} + 1.09997$, and imposing this is equal to u_0 we obtain $u_{o,0} = 0.66 - 1.09997 = -0.4397$. For *wind* we set $u_w(t = 0) = u_{w,0} + \rho x_{w,0} - x_{w,0}^{-0.1} = u_0$, or $u_{w,0} = 0.66 - 2 \times 0.09 + 0.09^{-0.1}$, obtaining $u_{w,0} = 1.7523$. Finally, for *solar* we set $u_s(t = 0) = u_{s,0} + \rho x_{s,0} - x_{w,0}^{-0.2} = u_0$, or $u_{s,0} = 0.66 - 2 \times 0.03 + 0.03^{-0.2}$, obtaining $u_{s,0} = 2.6164$.

(III) ***Climate policies***. We consider five climate policies and use the initial utility setting of scenario I, reflecting distinct initial profitability of energy sources:

A. ***Carbon tax***. This is a tax proportional to the carbon content of fossil fuels, which is equivalent to a CO_2 emission tax (more difficult to monitor). We consider a low and a high value of the tax, $\tau = 33\$/tCO_2$ and $\tau = 125\$/tCO_2$, as discussed in Section 3.

B. ***Removal of existing fossil fuel market subsidies***. This intervention is obtained with negative values of σ_o^M and σ_c^M. These are parameters for which the empirical basis is weakest, as the impact of subsidies for fossil fuels is difficult to estimate. We consider the following opposite cases: [8]

B1. **removal of subsidies for *coal*** only, with $\sigma_c^M = -0.99$ and $\sigma_o^M = 0$.

B2. **removal of subsidies for both fossil fuels**, with $\sigma_c^M = \sigma_o^M = -0.99$.

C. ***Market adoption subsidies for renewables***. If market subsidies for renewables are already in place, here they are raised. The outcome of this scenario will be compared especially with that of the scenario with an emission tax (III.A), as these two are (imperfectly) substitute policies. We consider three sub-cases:

C1. **both renewables market subsidies** are raised, with $\sigma_w^M = \sigma_s^M = 7$;

C2. **only *solar* market subsidies** are raised, with $\sigma_s^M = 7$ and $\sigma_w^M = 0$;

C3. **only *wind* market subsidies** are raised, with $\sigma_w^M = 7$ and $\sigma_s^M = 0$.

D. ***R&D subsidies for renewables***. The learning factor of renewables is enhanced by $R\&D$ subsidies financed by revenues from a complementary emission tax, as formalised in Eq. (8). We consider the low and high values of τ mentioned in scenario III.A:

D1. **fixed allocation** of $R\&D$ subsidies for renewables (parameter γ constant in Equations 8);

D2. **dynamic allocation** of subsidies weighted by renewables' market shares, with $\gamma = \frac{x_s}{x_s + x_w}$ in Eq. (8).

E. ***Policy package***. We combine all policy factors studied above to meet the goal of less than 2^oC climate change, with $\tau > 0$, $\sigma_a^R > 0$ and $\sigma_a^M > 0$ for $a = solar, wind$ and $\sigma_b^M < 0$ for $b = coal, oil/gas$. This allows us to check if there is some combination of settings that reaches the target with a lower carbon tax than suggested by the outcome of scenarios III.A and III.D. If so, this might mean a more politically feasible policy.

4.2 Simulations of policy scenarios

We report in table 1 the final outcomes (year 2050) of different simulation scenarios, together with a description of the uncertainty of outcomes within each scenario at the end of the simulation. Later on, we provide simulated time series for market shares and emissions in each scenario, and we comment results in detail.

[8] The coefficients $\rho(1 + \sigma_o^M)$ and $\rho(1 + \sigma_c^M)$ in Equations (4-5) are assumed to be positive under any choice of parameters, in order for the market shares to satisfy increasing returns on adoption also after the removal of current subsidies.

Table 1: Summary of results in different simulation scenarios

Scenario	Market-shares ($x_{coal}, x_{oil/gas}, x_{solar}, x_{wind}$)	Transition to renewables?	Time-to-reach carbon budget	Uncertainty
I. BAU	$(72\%, 27\%, 0.5\%, 0.5\%)$	NO	15.1 years	none
II. Silver Bullet	$(0\%, 0\%, 100\%, 0\%)$	YES	NEVER	none
III.A low Carbon tax	$(66\%, 28\%, 4 \pm 1\%, 2\%)$	NO	15.2 years	1% range for *solar*
III.A high Carbon tax	$(0\%, 20\%, 77\%, 3 \pm 1\%)$	YES	22.3 years	1% range for *wind*
III.B1 removal of *coal* existing subsidies	$(40 \pm 4\%, 30\%, 26 \pm 4\%, 4\%)$	YES	15.1 years	4% range for *coal* and *solar*
III.B2 removal of *coal* and *oil/gas* existing subsidies	$(16 \pm 3\%, 5\%, 78 \pm 5\%, 1\%)$	YES	16.5 to 24.5 years	3% *coal* range, 5% *solar*, and 8 years range of time-2^oC
III.C1 market subsidies *solar*, *wind*	$(70\%, 28\%, 2\%, 0\%)$ in six cases, $(51\%, 28\%, 21\%, 0\%)$ in one case, $(29\%, 28\%, 43\%, 0\%)$ in one case, $(0\%, 0\%, 0\%, 100\%)$ in two cases	YES in four cases, NO in six cases	NEVER if *wind* wins, 15.1 years if *coal*, *solar*	different equilibria selected, *coal* mostly, *oil/gas* never
III.C2 market subsidies for *solar*	$(71\%, 27\%, 2\%, 0\%)$ in eight cases, $(32\%, 27\%, 41\%, 0\%)$ in one case, $(10\%, 27\%, 63\%, 0\%)$ in one case	YES in two cases, NO in eight cases	NEVER if *wind* wins, 15.1 years if *coal*, *solar*	different equilibria selected, *coal* mostly, *oil/gas* never
III.C3 market subsidies for *wind*	$(72\%, 27\%, .5\%, .5\%)$ in eight cases, $(0\%, 0\%, 0\%, 100\%)$ in two cases	YES in two cases, NO in eight cases	NEVER if *wind* wins, 15.1 years if *coal*, *solar*	different equilibria selected, *coal* mostly, *oil/gas* never
III.D1 *R&D* subsidies for renewables, fixed (50%) allocation, low carbon tax	$(2\%, 21\%, 16\% - 57\%, 20\% - 61\%)$	YES	21.1 years	*solar* or *wind* win, equilibrium selection slow, 40% variability of shares; very small variability of time-2^oC
III.D1 *R&D* subsidies for renewables, fixed (50%) allocation, high tax	$(0\%, 1\%, 99\%, 0\%)$ in two cases, $(0\%, 1\%, 0\%, 9\%)$ in eight cases	YES	NEVER	equilibrium selection for *solar* / *wind* overtaking the market
III.D2 *R&D* subsidies for renewables, fixed (50%) allocation, low carbon tax	$(2\%, 21\%, 11\% - 56\%, 21\% - 66\%)$	YES	21.1 years	*solar* or *wind* win, equilibrium selection slow, 40% variability of shares; very small variability of time-2^oC
III.D2 *R&D* subsidies for renewables, fixed (50%) allocation, high tax	$(0\%, 1\%, 99\%, 0\%)$ in two cases, $(0\%, 1\%, 0\%, 9\%)$ in eight cases	YES	NEVER	equilibrium selection for *solar* / *wind* overtaking the market
III.E Policy package	$(1 \pm 1\%, 4 \pm 2\%, 1\% - 93\%, 3\% - 97\%)$	YES	NEVER	equilibrium selection (possibly slow) of *solar* and *wind* with share range $> 90\%$, cumulative emissions range $0.3 \times 10^{12} tCO_2$

These are final outcomes in the year 2050. In particular, the column "Transition to renewables?" reports whether or not a convergence pattern realises towards the equilibrium with *solar* or *wind* as primary energy sources. The column "Uncertainty" reports the range of markets shares in 2050 across 10 simulation runs if only one equilibrium is achieved; alternatively, it reports the different equilibria that are reached in terms of dominant energy source.

Scenario I: Business as Usual (BAU)

In the BAU scenario the initial utility values are ranked as $u_o(t=0) > u_c(t=0) > u_w(t=0) > u_s(t=0)$. Figure 3 reports the time series of market shares of energy sources for the case without any climate policy (here x_{oil} is for *oil* and *gas* together). The main feature of

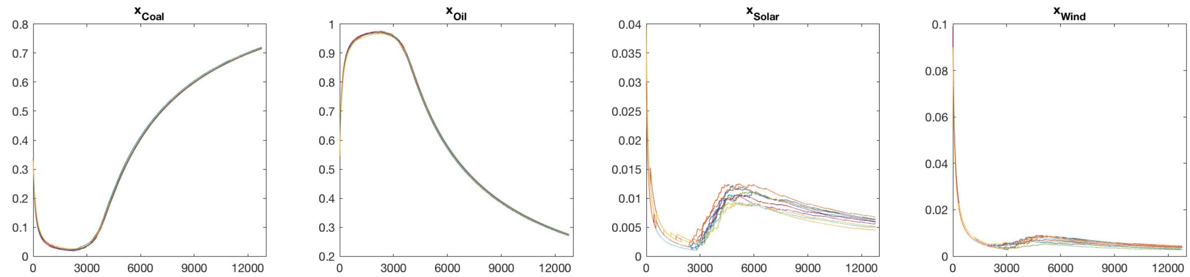

Figure 3: Market shares of the four energy sources (10 simulations in different colours). Scenario (I): BAU. The horizontal axis is number of days (time horizon 35 years). Notice a different scale of the vertical axis in the panels.

the simulations in this scenario is the non-monotonic pattern of *oil/gas* share that peaks at around $t = 2000$, corresponding to about 5.5 years. Initially *oil/gas* surges thanks to the strong increasing return to adoption from its larger initial market share. This expansion is progressively hampered by the peak oil term in utility (5). When *oil/gas* starts to decline, the other three energy sources rebound and their shares increase. However, renewables' rebound is short-lived: their utility becomes larger than *oil/gas*, but not of *coal*, and their shares peak at a time around $t = 4000$ (11 years). The winning energy source in this scenario is *coal*, whose market share rebounds around $t = 3000$ and conquers the energy market, reaching a share larger than 70% at the end of the simulation time horizon.

This pattern of energy market shares has particular implications for average CO_2 emission intensity, which increases sharply after the rise of *coal*, and for cumulative emissions, as shown in Figure 4.

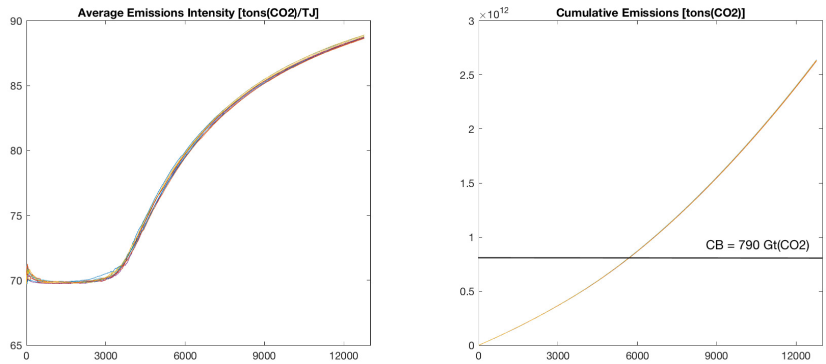

Figure 4: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Scenario (I): BAU. The horizontal axis reports time in days (time horizon of 35 years).

Under the *laissez-faire* approach of the BAU scenario there is essentially a substitution from *oil/gas* to *coal*, induced by the peak-oil effect. As a consequence, cumulated emissions reach the 2^oC carbon budget around 2030, and then increase far beyond.

Scenario II: Silver Bullet Policy

A "Silver Bullet" scenario, albeit unrealistic, serves as a useful benchmark, as it shows energy share dynamics if a technological breakthrough would assure instantaneous equal profitability of fossil fuels and renewables. Figure 5 shows a sudden diffusion of the *solar* source, which ends up prevailing over fossil fuels and *wind*. After only 5 years,

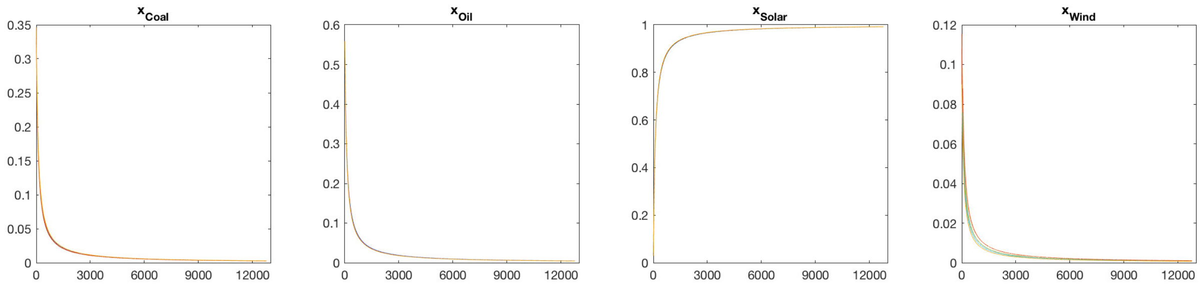

Figure 5: Market shares of the four energy sources (10 simulation runs, in different colours). Scenario (II), Silver Bullet policy: energy sources equally attractive at the start, $u_o(t = 0) = u_c(t = 0) = u_w(t = 0) = u_s(t = 0) = u_0$. The horizontal axis reports time in days (time horizon of 35 years). Notice the different scale of the vertical axis.

solar represents more than 90% of energy choices. This translates in strongly declining figures for emissions intensity (Figure 6, left panel) As a result, cumulative emissions

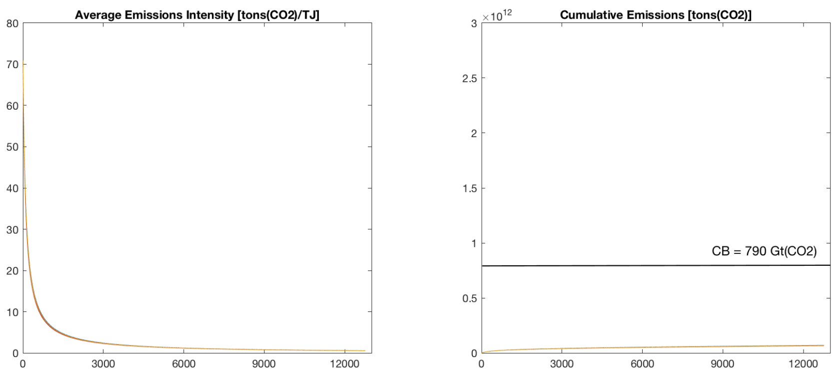

Figure 6: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Scenario (II), Silver Bullet policy: the four energy sources are made equally attractive at the start, with $u_o(t = 0) = u_c(t = 0) = u_w(t = 0) = u_s(t = 0) = u_0$. The horizontal axis reports time in days (time horizon of 35 years).

stabilise (Figure 6, right panel), remaining well below the carbon budget of 790 $Gt(CO_2)$. The reason for the dominance of *solar* is its superior learning rate. Positive feedback of increasing returns to adoption magnifies the attractiveness of *solar* early on.

Scenario III.A: Emission Tax

We consider now a carbon tax, with a low and a high tax level, $33\$/tCO_2$ and $125\$/tCO_2$ respectively, as introduced in Section 3. Figures 7 and 8 allow to compare the results.

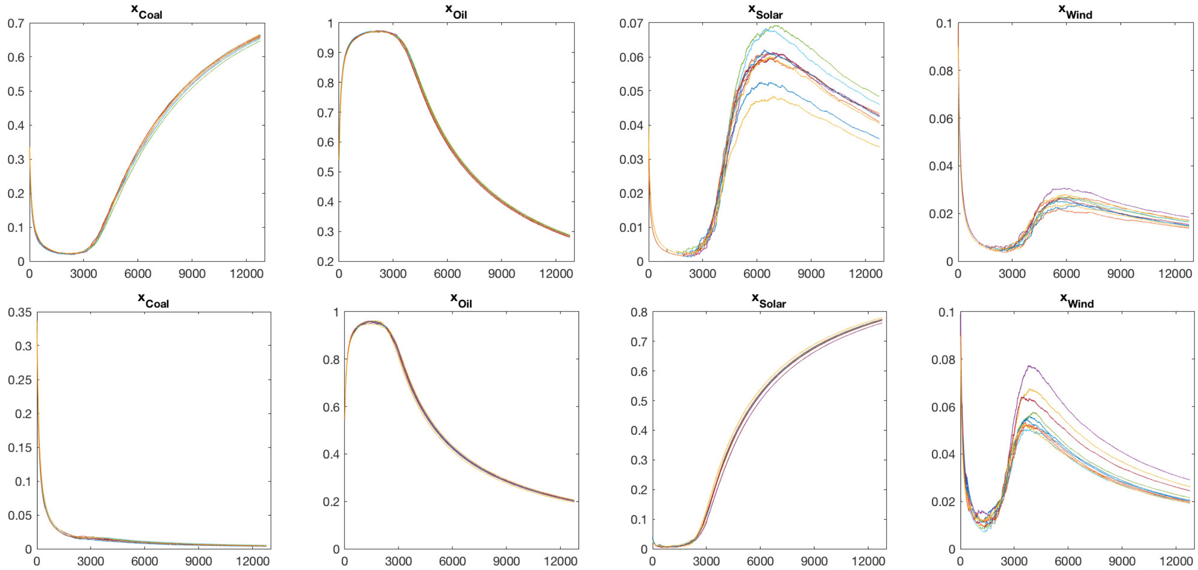

Figure 7: Market shares of the four energy sources (10 simulation runs, in different colours). Scenario (III.A): Emission Tax, with a price of carbon equal to $33\$/tCO_2$ (upper panels) and $125\$/tCO_2$ (lower panels). The horizontal axis reports time in days (time horizon of 35 years). Notice the different scales of the vertical axis.

The low tax results (upper panels) do not differ much from the BAU scenario (Figures 3 and 4). The high tax level instead (lower panels) causes a sharp decrease of *coal*, and a transition from *oil/gas* to *solar*, which attains a market share of almost 80% at the end of the time horizon. *Wind* reaches a modest share of $5-8\%$ and then declines, being unable to compete with *solar* due to a lower learning rate.

A first result from the analysis of this scenario is that, depending on the tax rate, we may either or not escape the undesirable transition to *coal* of scenario I. In particular, for the two different calibrations of the tax rate that we consider, only the higher rate of $125\$/tCO_2$ avoids the BAU outcome with a peak oil pattern followed by a lock-in into the dominance of *coal*. A low tax rate is then completely ineffective.

The average emission intensity drops after the peak oil for a high tax level (Figure 8, lower panels), and cumulated emissions increase at a lower pace than under the BAU and the low tax level scenarios. As a consequence, the 2^oC carbon budget is exhausted later, after about 8000 days, or 22 years. However, if the aim of a climate policy is to stay below the carbon budget, also the high tax level fails. The outcome is merely an extension of the time when the carbon budget is reached of 7 years, with respect to BAU. The reason is that although the high tax triggers a transition to *solar*, the decrease of fossil fuel market shares is slow. It is only after about 5000 days - almost 14 years - that

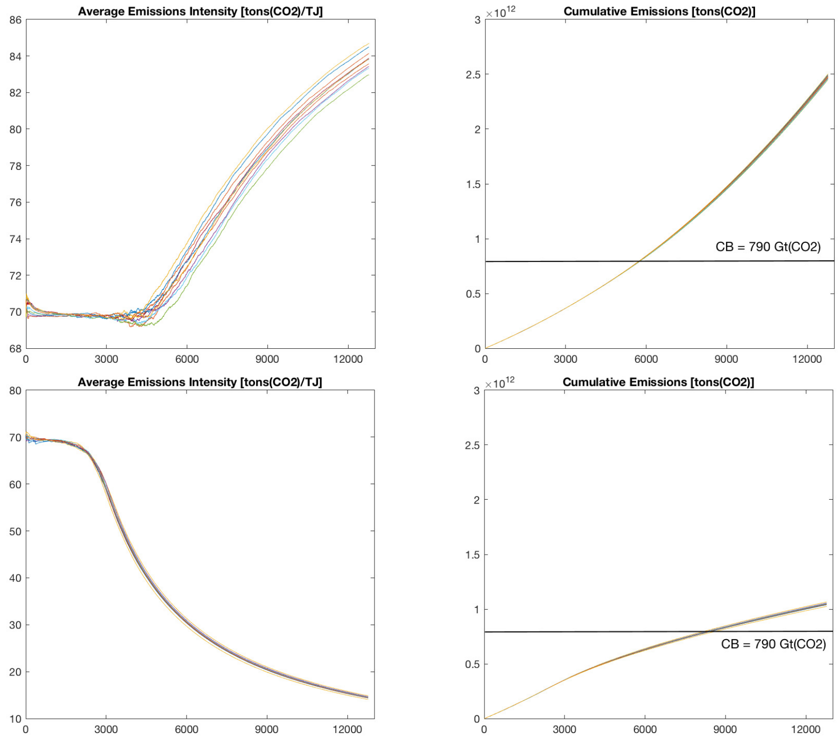

Figure 8: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Scenario (III.A): Emission Tax, with a price of carbon equal to $33\$/tCO_2$ (upper panels) and $125\$/tCO_2$ (lower panels). The horizontal axis reports time in days (time horizon of 35 years).

solar overcomes *oil/gas*. As a result, CO_2 emissions continue to accumulate substantially in the atmosphere, and the carbon budget is reached only slightly later.

Values of the emission tax τ in between the low and high levels considered result in a transition between the two different long run equilibria presented above, and is characterised by high uncertainty. There is a critical level of the emission tax, around $45\$/tCO_2$ that presents a large variability of outcomes: some simulations runs show a slow transition to *solar*, while some other present a transition to *coal*. However, this variability affects cumulated emissions only in the final part of the time horizon, and the time when the carbon budget is reached is almost unaffected.

In order to understand the criticality of the emission tax in setting the transition to *solar*, we simulate the model for an intermediate level of this tax, namely $45\$/tCO_2$. The competition dynamics from this model setting is characterised by a huge variability of outcomes. In particular, either *solar* or *coal* may become the dominant energy source in the long run (Figure 9). This is the result of the emission tax being at a critical level represented by the separation between different basins of attractions of this model with multiple equilibria. As pointed out in Section 2, four different equilibria are possible, where each one of the four energy source dominates the market. The values of parameters

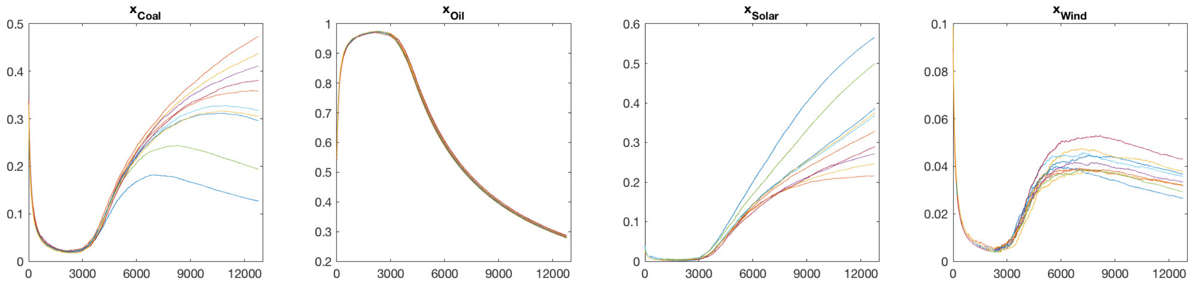

Figure 9: Market shares of the four energy sources (10 simulation runs, in different colours). Scenario (III.A): Emission Tax, with a price of carbon equal to $45\$/tCO_2$. The horizontal axis reports time in days (time horizon of 35 years). Notice the different scale of the vertical axis in the four panels.

determine the separation between the basins of attractions of these equilibria. If we set the value of one parameter, the emission tax in this case, at a critical level, where the initial condition of the model (the initial market shares) is close to the separation of the basins of attraction of two equilibria, the outcome is what we see in this scenario: due to the randomness of the sequential decision model, sometimes the decision patterns falls into the basin of attraction of one equilibrium (e.g. the one of *solar*), while some other times it falls into the other basin (e.g. *coal*). The criticality of a parameter like the emission tax is a distinguishing feature of our model. Beside presenting multiple equilibria, in our model the transitory dynamics of the sequential decision system shows how it can happen that one equilibrium or another is attained, with huge implications for environmental policies. If policy channels like emission taxes are set at a critical level, the resulting long run outcome is unpredictable.

This critical scenario is reflected by CO_2 emissions. After the first 4000 days (about 11 years) the average emission intensity under different simulations diverges to very different levels, with emissions increasing whenever *coal* becomes dominant, and decreasing if *solar* becomes dominant (Figure 10, left panel). On the other hand, cumulative emissions are not

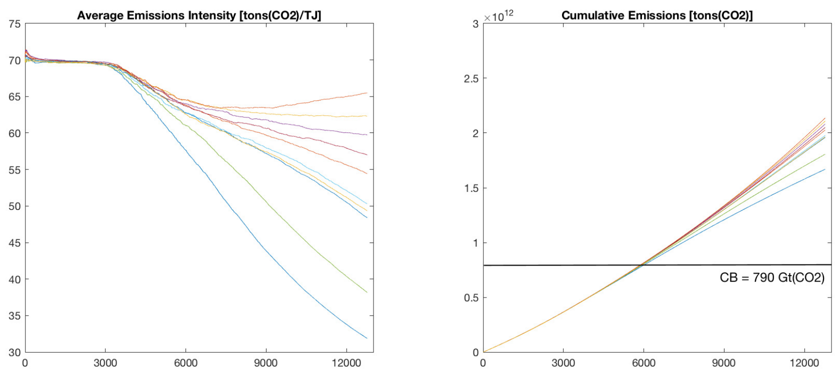

Figure 10: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Scenario (III.A): Emission Tax, with a price of carbon equal to $45\$/tCO_2$. The horizontal axis reports time in days (time horizon of 35 years).

much affected by this large variability of outcomes. The time series of different simulation runs only diverge late in the time horizon, and after the stock of emissions exhausts the carbon budget. This occurs only slightly later than with $33\$/tCO_2$, around 6000 days, or 16.5 years (Figure 10, right panel).

Concluding, these simulations show that a carbon tax should be high in order to be effective. If it is too low, the tax induces an undesirable transition to *coal* instead of renewables. If only moderately large, it presents a huge variability of outcomes in terms of leading energy source, and moreover this is accompanied with scarce results in terms of cumulated emissions.

Scenario III.B: Removal of existing fossil fuel market subsidies

In Scenario I (BAU) it is assumed that fossil fuels enjoy subsidies that contribute to increasing returns to adoption. Here we consider the removal of such subsidies. This is described as a 99% reduction of the increasing return to adoption term of their profitability (the second term of utility in Eq. 4 and Eq. 5). This is obtained by setting a value of σ_c^M and/or σ_o^M equal to -0.99. We recognize that such a value is a bit arbitrary, as we are not able to provide a firm empirical basis for this parameter. We also tried lower values, which had little impact because the initial dominance of fossil fuels along with increasing returns leads to their long term dominance.

We consider two cases: the removal of subsidies for *coal* only given that it has the highest carbon intensity (scenario III.B1), and the removal of subsidies for both fossil fuels (scenario III.B2). Figure 11 compares the results in terms of competition dynamics.

In Scenario (III.B1) we observe a peak oil pattern (middle-left upper panel) identical to the BAU scenario, followed by a temporary transition to *coal* (left upper panel), which in turn starts declining after 11000 - 12000 days (30 - 33 years). This is when *solar* shares start increasing (middle-right upper panel). On the other hand, *wind* remains marginal in this scenario. and *solar* is the winning energy source in the long run. The same qualitative result obtains in Scenario (III.B2), but much more rapidly (lower panels).

There are two phases in this transition pattern: first a (undesired) shift from *oil/gas* to *coal*, and later a transition from *coal* to *solar*. As a result, the emissions intensity presents a non-monotonic pattern (Figure 12): in Scenario III.B1 it is essentially constant for the first 3000 days (about 8 years), then it increases following the surge in *coal.* After peaking around 6000 days (16.5 years) the emission intensity decreases (Figure 12, upper-left panel). The upper-right panel of Figure 12 shows that the carbon budget is exhausted almost at the same time as in the BAU scenario. There are two reasons behind this outcome: first, the transition to renewables (*solar* in this case) occurs too late; second, it

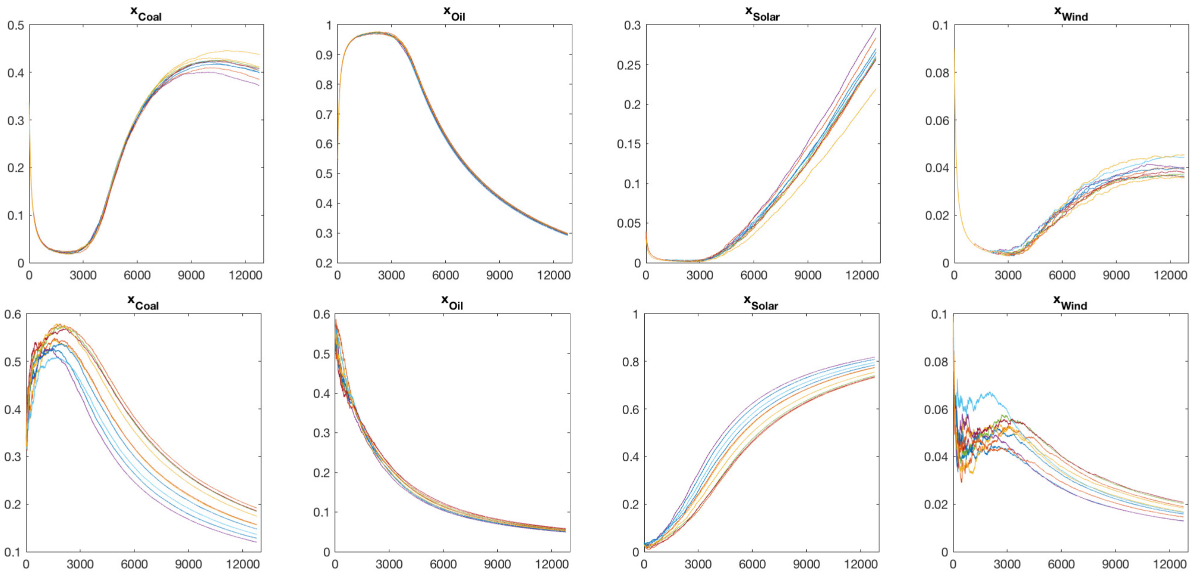

Figure 11: Market shares of the four energy sources (10 simulation runs, in different colours). Upper panels, Scenario (III.B1): market subsidies removal for *coal* only, with $\sigma_c^M = -0.99$, $\sigma_o^M = 0$. Lower panels, Scenario (III.B2): market subsidies removal for both *coal* and *oil/gas*, with $\sigma_o^M = \sigma_c^M = -0.99$.The horizontal axis reports time in days (time horizon of 35 years). Notice the different scale of the vertical axis in the four panels.

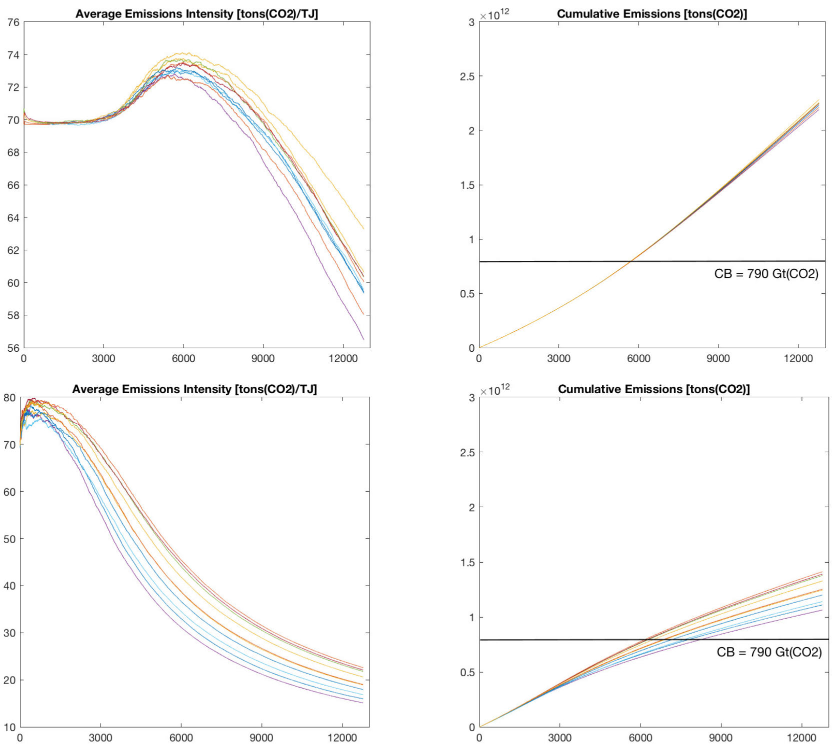

Figure 12: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Upper panels, Scenario (III.B1): removal of *coal* market subsidies, with $\sigma_c^M = -0.99$, $\sigma_o^M = 0$. Lower panels, Scenario (III.B2): removal of *coal* and *oil/gas* market subsidies, with $\sigma_o^M = \sigma_c^M = -0.99$. The horizontal axis reports time in days (time horizon of 35 years).

is preceded by a temporary transition to *coal*.

The outcome of this policy intervention in terms of emission intensity does not improve much with a complete removal of fossil fuel subsidies (Scenario III.B2). The average emission intensity starts decreasing much earlier (Figure 12, lower-left panel), but not fast enough to produce significantly lower cumulative emissions. Now we observe some variability across simulation runs, with the carbon budget reached between 6000 and 9000 days (16.5 and 24.5 years, respectively).

Concluding, the removal of fossil fuel market subsidies shows limited potential as a climate policy. Even the most extreme case (Scenario III.B2) obtains only a delay of no more than 10 years for the carbon budget to be exhausted, compared to the BAU. This should be no surprise if one realises that the overall social cost of fossil fuel subsidies is likely of an order of magnitude of 10% of that of the total external cost of carbon if the latter is valued against a high estimate of the per unit social cost of carbon (SCC) (e.g., the 125$/$tCO_2$ used here). Unfortunately, studies have raised high expectations by comparing them for lower SCC values, causing the relative importance of fossil fuel subsidies to be inflated (Coady et al., 2015).

Scenario III.C: Subsidies for market adoption of renewables

Now we explore the effect of an increased level of subsidies for renewable energy sources. For values of σ_s^M and σ_w^M equal to 6 or below (Equations 6-7) simulated trajectories are almost identical to Scenario I. Above that level results start to change. This means that in our model this channel of subsidies needs to make increasing returns on adoption for renewables at least seven times as large as for fossil fuels in order to be effective.

With a subsidy $\sigma_s^M = \sigma_w^M = 7$ (Figure 13, upper panels) we observe different trajectories across simulation runs, with three different possible outcomes. In this example, in one instance *wind* overtakes the market, while in two other runs *solar* is the winning technology. In the remaining cases, *coal* becomes dominant, like in the BAU scenario. The middle and lower panels of Figure 13 show that market subsidies work likewise when only one or two subsidies are present in that the resulting dynamics are similar.

The competition dynamics of this scenario presents a number of distinctive features: if *wind* overtakes the market it does so by displacing *oil/gas* in the early stages of the simulation. On the other hand, when *solar* is the winning energy source, we need to wait a longer time. Initially, *coal* replaces *oil/gas* after the peak-oil effect; later *solar* takes off: in one case this happens after about 7500 days (20.5 years), in another case after 9500 days (26 years). Resulting patterns of CO_2 emissions are strongly affected by the realised competition outcome. Average emission intensity drops very quickly when *wind* prevails, but much later when *solar* prevails (Figure 14, left panel). As a consequence,

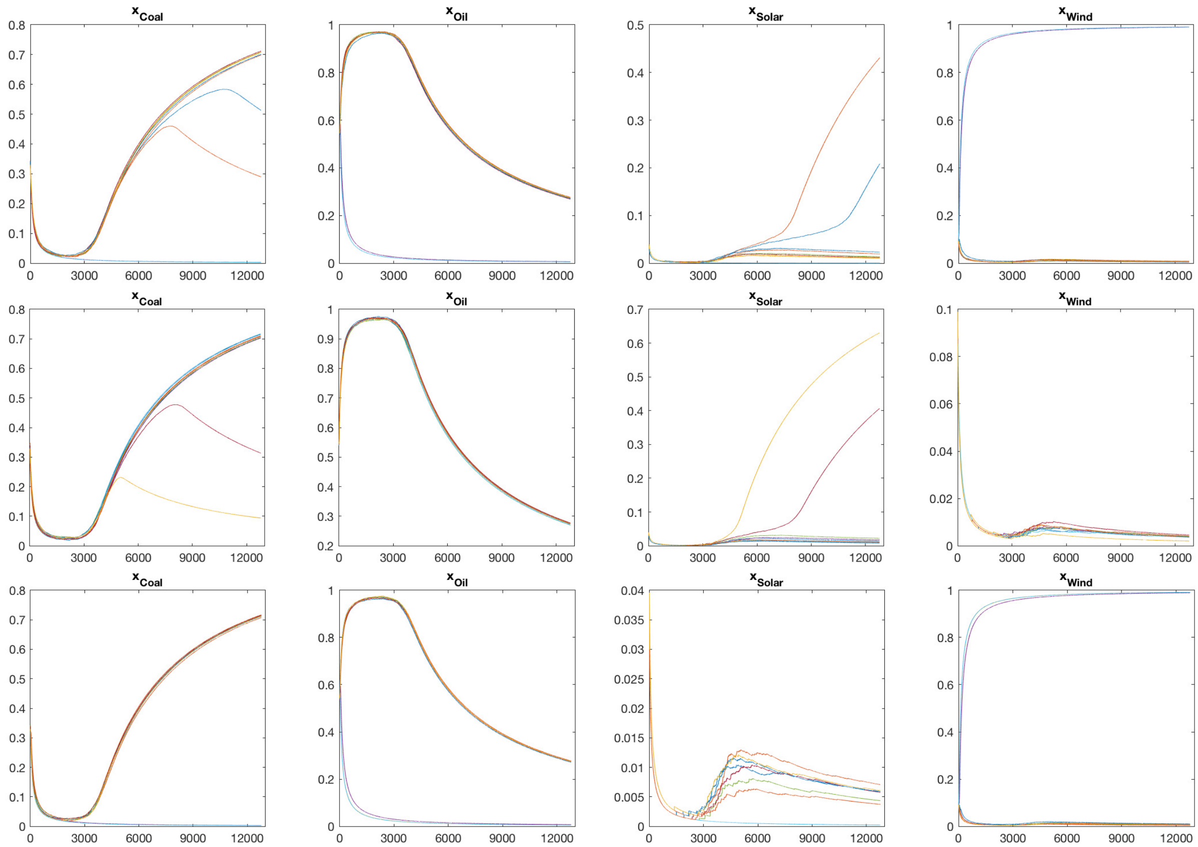

Figure 13: Market shares of energy sources (10 simulation runs, in different colours). Upper panels: market subsidies for both renewables (III.C1), with $\sigma_s^M = \sigma_w^M = 7$. Middle panels: market subsidies only for *solar* (III.C2), with $\sigma_s^M = 7$, $\sigma_w^M = 0$. Lower panels: market subsidies only for *wind* (III.C3), with $\sigma_w^M = 7$. The horizontal axis reports time in days (time horizon of 35 years). Notice the different scale of the vertical axis in the four panels.

cumulated emissions stay well below the carbon budget level only when *wind* results to be the winner (Figure 14, right panel). A transition to *solar* in this scenario does not avoid the carbon budget of 790 $Gt(CO_2)$ to be exhausted almost at the same time as in the BAU scenario. Cumulated emissions diverge only marginally and quite late in the time-horizon considered.

The results illustrate that market subsidies for *wind* are ineffective after the early stages of the simulation, while market subsidies for *solar* work in combination with learning. If the objective is to favour a transition to any renewables, one best devotes investment to only one of the two, to make its fortune more likely. However, if the policy objective is to avoid the carbon budget to be exhausted, *wind* is the energy source that should be subsidised. *Solar* becomes attractive only through learning, but this takes time.

The learning factor of *solar* and *wind* works as a "slowly-varying parameter", that describes a change of the decision environment that tales place at a time scale much slower than the time scale of decisions (daily). In particular, since learning is stronger for *solar*, it is for this technology that we observe a late transition, and not for *wind*. The cases

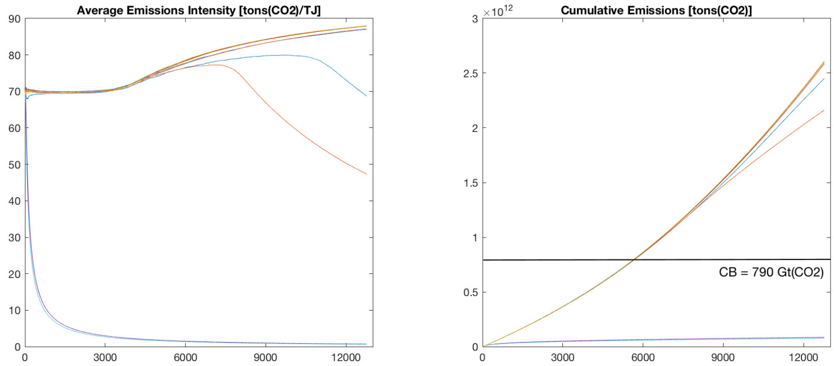

Figure 14: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Scenario (III.C1): increased market subsidies for renewables, with $\sigma_s^M = \sigma_w^M = 7$. The horizontal axis reports time in days (time horizon of 35 years).

when *wind* wins refer to situations where, since the profitability of this one and *oil/gas* is comparable at start, early decisions can change the fate of the entire simulations, as it is typical in Polya urn models (Arthur et al., 1987; Arthur, 1989).

Scenario III.D: R&D subsidies for renewables

We consider here subsidies for renewable energy R&D, that enhance their learning factor (Equations 6 and 7). As described by Eq. (8), R&D subsidies are financed by the revenues of an emission tax proportional to emissions of fossil fuels (see Scenario III.A). Since this is a dynamic factor that varies with the market shares of *coal* and *oil/gas* innovation subsidies also involve time dynamics.

We implement an even allocation of tax revenues to *solar* and *wind R&D*, by setting $\gamma = 0.5$ (Scenario D1). This is motivated by the idea that it is wise to keep all options open in the face of uncertainty about innovation dynamics for the two energy sources. We find that for the lower carbon tax level $\tau = 33\$/tCO_2$ the competition dynamics presents a large variability (Figure 15, upper panels): after a peak-oil effect, different outcomes can result, with market shares trajectories of *solar* and *wind* that vary substantially across different simulation runs. Randomness here involves the selection of one out of two long run equilibria which are attainable in this setting: either one of the two renewable sources here prevail. Moreover, the speed at which equilibrium selection occurs is subject to randomness as well, and consequently the duration of the delayed peak for the other renewable varies, first growing, and then slowly retreating. We observe in the first example of Figure 15 (upper panels) that half of the simulations are heading to the equilibrium where *wind* prevails, and half to *solar* prevailing.

The reason behind such variability of results is twofold. One factor is stochasticity of the sequential decision mechanism, as in Arthur et al. (1987). In addition, technological

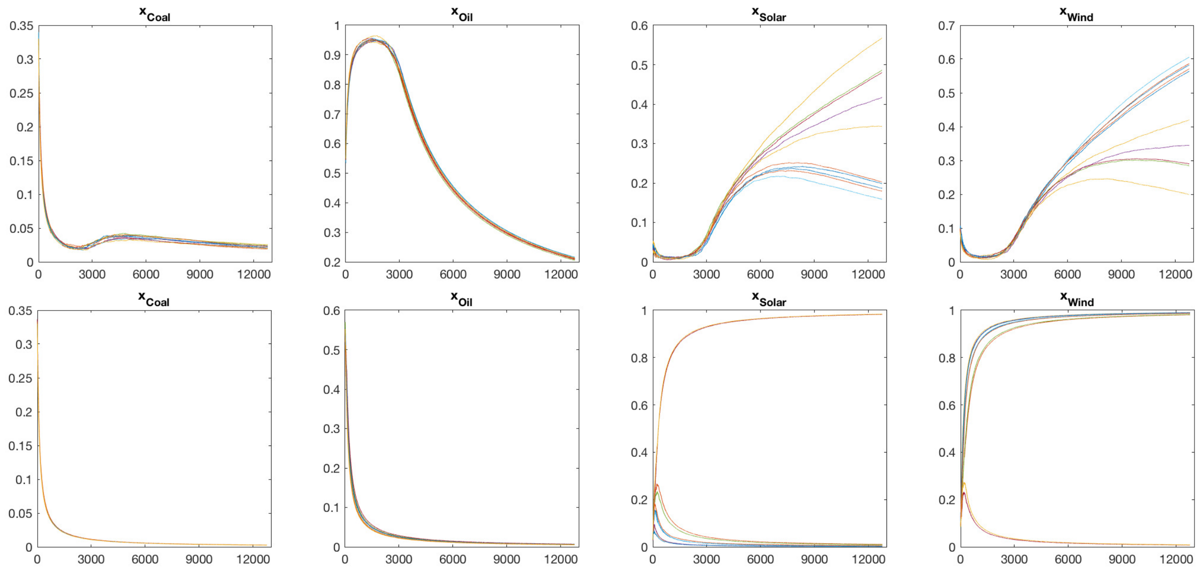

Figure 15: Market shares of the four energy sources (10 simulation runs, in different colours). Scenario (III.D1) with even allocation of R&D subsidies for *solar* and *wind* ($\gamma = 0.5$). Upper panels: carbon tax $\tau = 33\$/tCO_2$. Lower panels: carbon tax $\tau = 125\$/tCO_2$. The horizontal axis reports time in days (time horizon of 35 years). Notice the different scale of the vertical axis in the four panels.

progress plays a role: learning can make two options with distinct performance comparable at a late stage of the simulation. With the low level of carbon tax equilibrium selection between *solar* and *wind* occurs here only after about 15 years. While little difference in market shares across simulations is observable before for *solar* and *wind*, they end up with market shares that vary between 20% and 50% at the end of the time horizon (35 years). The high level of the carbon tax gives equilibrium selection much earlier, almost at the beginning of the simulation time horizon. In this case we observe a bimodal distribution of outcomes. Here uncertainty is about which renewable prevails between *solar* and *wind*, but there is very little variability in each of this two outcomes, as the winning energy source dominates the market in all simulation runs.

Despite the rich competition dynamics of market shares, CO_2 emissions measures show very little variability, instead. The average emission intensity reported in the upper-left panel of Figure 16 is fairly stable for the duration of the peak oil (about 3000 days, or 8 years) and then declines. Regarding cumulated emissions (Figure 16, upper-right panel), the 2^oC carbon budget is exhausted after about 7700 days, or 21 years, which is only 7 years later than in the BAU scenario.

The simulations for the higher tax level of $125\$/tCO_2$ offer a brighter picture. The competition dynamics now is much faster (Figure 15, lower panels), and either *wind* or *solar* get to dominate the energy market very rapidly. As a consequence, CO_2 emissions intensity is sharply decreasing in the early stages of the time horizon already (Figure 16, lower-left panel), and cumulated emissions remain very low and far below the carbon

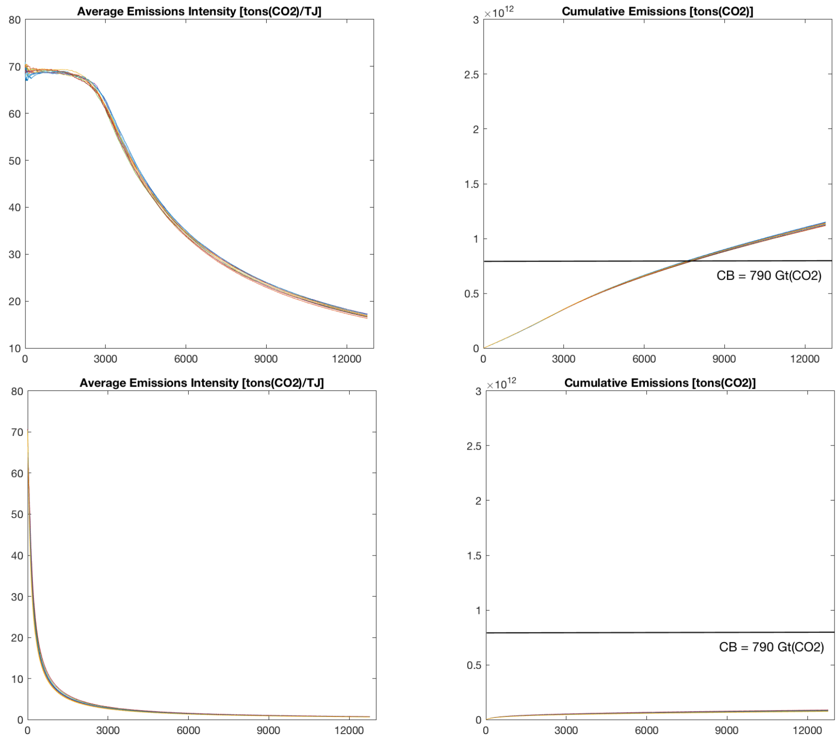

Figure 16: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Even allocation of R&D subsidies for *solar* and *wind* ($\gamma = 0.5$ in Eq. 8). Upper panels: carbon tax $\tau = 33\$/tCO_2$. Lower panels: carbon tax $\tau = 125\$/tCO_2$. The horizontal axis reports time in days (time horizon of 35 years).

budget (Figure 16, lower-right panel).

Different allocation weights γ of emission tax revenues to renewables $R\&D$ only affect the internal competition dynamics of *solar* and *wind*, but do not substantially alter the overall outcome in terms of CO_2 emissions abatement. This depends almost totally on the emission tax level.

We can compare the present policy scenario with Scenario III.A, which only implements an emission tax. In scenario III.A the low emission tax $33\$/tCO_2$ is not able to grant a long run transition to renewables, with *solar* only experiencing a temporary peak (Figure 7, upper panels). In the present scenario instead even the low tax level fosters a transition to either *solar* or *wind* for $\gamma = 0.5$ (Figure 15). The high emission tax $125\$/tCO_2$ in Scenario III.A does trigger a transition to *solar*, but this is too slow to avoid cumulated emissions exhausting the carbon budget in the foreseeable future (Figure 8, lower panels). Instead, the reinvestment of tax revenues to *solar* and *wind* in the present scenario keeps cumulated emissions below the carbon budget by a very large extent, when we use a price of carbon equal to $125\$/tCO_2$ for the tax rate (Figure 16, lower panels).

A variant of this policy scenario is one where the allocation parameter γ is not fixed, but set dynamically according to the realised market shares of *solar* and *wind*, with the ratio $\frac{x_s}{x_s+x_w}$ (Scenario D2). Over time, the allocation γ in renewables' learning factor (Eq. 8) is updated accordingly. This setting provides a feedback mechanism in the model that makes such policy adaptive. But despite the dynamic complexity of the mechanism, the results are strikingly similar to the 50-50 allocation just analysed (see Appendix B).

Scenario III.E: Policy package

Here we examine if less stringent instrument settings can in combination serve as an effective climate policy, i.e. avoiding to surpass the carbon budget. Laxer instrument settings potentially may be counting on broader social and political support, as opposed to a very high carbon tax which might do the same job. We combine a carbon tax, reduction of fossil fuel subsidies, and market and *R&D* subsidies for renewables. We observe that a

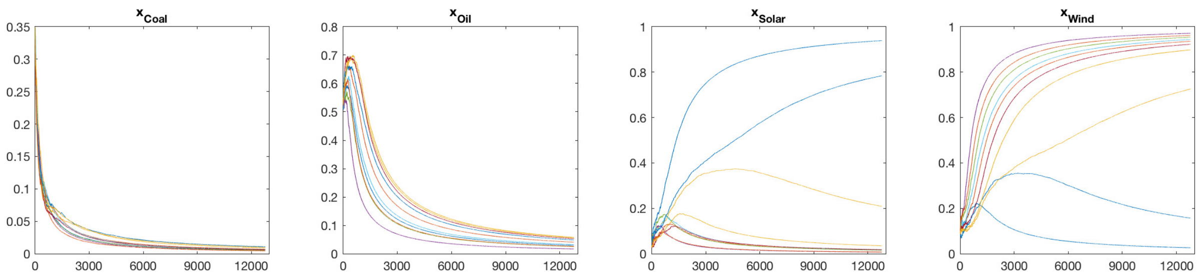

Figure 17: Market shares of the four energy sources (10 simulation runs, in different colours). Scenario (III.E): dynamic allocation of *R&D* subsidies for *solar* and *wind* ($\gamma = \frac{x_s}{x_s+x_w}$), with a price of carbon equal to $33\$/tCO_2$, together with a reduction of fossil fuel subsidies by 30%, with $\sigma_c^M = \sigma_o^M = -0.3$. The horizontal axis reports time in days (time horizon of 35 years). Notice the different scale of the vertical axis in the four panels.

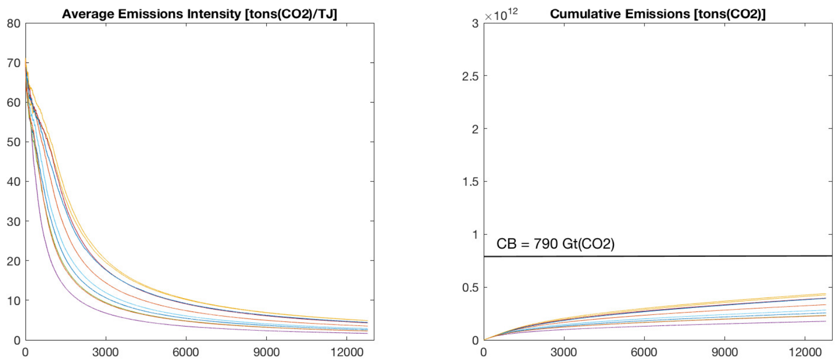

Figure 18: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Scenario (III.D2): dynamic allocation of R&D subsidies for *solar* and *wind* ($\gamma = \frac{x_s}{x_s+x_w}$), with a price of carbon equal to $33\$/tCO_2$, together with a reduction of fossil fuel subsidies by 30%, with $\sigma_c^M = \sigma_o^M = -0.3$. The horizontal axis reports time in days (time horizon of 35 years).

lower reduction of fossil fuel subsidies (namely less than 1/3) is sufficient in combination with *R&D* subsidies funded by the lower carbon tax to enforce a transition to one or the other renewable energy source. What is more important, such a transition occurs early enough to keep emissions below the carbon budget. There is some variability of results across simulation runs, reflecting uncertainty regarding the time when cumulative emissions would cross the carbon budget line.

The intuition for why this combination of policies delivers an effective policy outcome is that by lowering the initial attractiveness (utility) of fossil fuels, the reduction of subsidies compensates for the initial disadvantage that renewables have due to their smaller installed capacity. A relatively small reduction is enough to make renewables competitive, and then learning makes the difference, driving a transition from fossil fuels to renewables.

5 Conclusions and Policy Implications

We have developed a novel stochastic decision model with learning curves and path-dependence to describe the competitive dynamics of *coal*, *oil/gas*, *solar* and *wind* energy sources under distinct climate policy settings. The choice of two fossil fuels and two renewable energy sources was motivated by the aim to create relevant variation in emission intensity, initial or current profitability, and learning or innovation potential.

The model is fairly simple and hence transparent, which is an advantage over more complex equilibrium models from economics or bottom-up technology models from energy studies. It is, nevertheless, sufficiently rich to analyse and compare a wide range of climate policies aimed at avoiding extreme global warming, defined here as exceeding a global average temperature of 2^oC. Such policies include a carbon tax, market adoption subsidies and *R&D*, innovation subsidies, and elimination of current fossil fuel support in the form of energy subsidies. The model approach, based on a probabilistic sequential decision mechanism, has the advantage of not only identifying long-run equilibria but also providing insight into transitory dynamics. This allows to accurately capture the dynamic impact of slowly-varying factors such as peak oil and learning in renewables.

The simulation results show that in many settings *solar* profitability increases and is able to stop the convergence to an equilibrium with *coal* being dominant to re-direct the system towards another equilibrium, namely with *solar* being dominant. The nature of the model allows us to derive information about transition patterns to a low-carbon energy system, the timing of surpassing the carbon budget associated with the 2^oC target, and the final market structure of energy supply. Our specific findings for the policy and other scenarios studied can be summarised as follows:

- Business as Usual (BAU): In the absence of climate policy, cumulative emissions will exhaust the carbon budget while peak energy effects will trigger a shift from *oil/gas* to *coal*, intensifying and accelerating global warming. The carbon budget is exhausted after a little over 15 years.

- "Silver bullet": Due to a technological breakthrough, without any time delay all renewables are perfectly cost-competitive with fossil fuels. This results in *solar* energy diffusing rapidly and ultimately taking over the entire market as it has the fastest learning rate, and in turn enjoys increasing returns to adoption.

- A carbon tax on fuels (equivalent to a CO2 emission tax): A low value of $33\$/tCO_2$ recommended by the US EPA does not make much of a difference compared to BAU. However, a high value of $125\$/tCO_2$, consistent with a meta-assessment of estimates of the social cost of carbon, makes a huge difference. It leads to phasing-out of coal, a strong reduction in *oil/gas* from about 80% to 20% market share, an increase of *solar* to almost 80% and a very low market share of *wind* in the range of 2-4% (uncertainty range).

- Removal of existing fossil fuel market subsidies: An equal reduction for *coal* and *oil/gas* results in peak-oil effects causing *coal* to dominate in the long run with a market share of almost 90%, while renewable remain jointly around 5%. If only *coal* subsidies are removed, then *coal* varies around 40%, *oil/gas* around 30%, *solar* around 25% and *wind* at almost 4%. In comparison with the other policy instruments, here the empirical basis is somewhat weaker as it is not precisely clear what the direct quantitative effect of removing subsidies will be on behaviour.

- Market adoption subsidies for renewables: If subsidies are equal for *solar* and *wind*, the result is very unstable. When *wind* overtakes the market it does so immediately, by displacing *oil/gas*. If *solar* does so, it takes considerably longer, while during the transition initially *coal* replaces *oil/gas* due to peak effects, and subsequently *solar* takes off due to learning and innovation effects. While uncertainty and instability do not disappear when only *solar* or *wind* adoption are subsidised, what is certain is that the non-subsidised alternative will not prosper. If the objective is to favour a transition to any renewable, the most effective strategy is to devote all subsidies to only one renewable option, as this will favour its fortunes. If the policy objective is, however, to avoid exhaustion of the carbon budget then *wind* adoption should be subsidised as *solar* needs more time to benefit from learning.

- Innovation (*R&D*) subsidies for renewables combined with a carbon tax to generate their revenues: With fixed allocation of the budget to *wind* and *solar* at each time, results differ between a low and high carbon tax. In the first with 50/50 subsidy budget allocation to *wind* and *solar*, a transition to renewables occurs but it is uncertain which of *solar* or *wind* ultimately dominates. In addition, *oil/gas* at the final time horizon still has a market share above 20%, although declining. Under a high carbon tax and innovation subsidies the transition to renewables is complete and swift, consistent with the literature in environmental economics which suggests this to be the most powerful combination of instruments to achieve a solution to climate change. But there is uncertainty about whether *solar* or *wind* will dominate in the end. With a dynamic allocation of the budget to *wind* and *solar*, to reflect the relative profitability due to installed capacity, very similar results are obtained. This suggests that a simple, static budget allocation rule is sufficient.

- Since several of the studied policies do not stabilise climate change, i.e. exceed the 2^oC carbon budget, while others requires stringent settings, we also considered all policies together. It shows that in this case weaker interventions for each instrument are sufficient, which might count on more voter and political support.

A main insight from our study is that only two combinations of policies can systematically keep cumulative CO_2 emissions within the carbon budget: namely, a high carbon tax with $R\&D$ subsidies for renewables; and a policy package with a lower carbon tax and elimination of existing fossil fuel subsidies. Of these, the latter has the advantage that it may be politically more feasible than the first.

While previous studies tend to focus on a subset of these instruments, and often adopt a static equilibrium framework, our study is able to compare or combine them all in an explicitly dynamic framework, thus allowing for a more complete analysis. Model analysis clarifies two features of climate policies: which ones solve the climate problem, i.e. maintain the economy within the carbon budget; and which market shares of energy sources result, and with which degree of uncertainty or variability.

The model was applied to a global scale, as climate change and energy markets both have an international scope. It could, though, be fairly easily adapted to deal with distinct sets of energy resources, or specific features of a region or country. The breadth of our approach comes at a cost, namely a fairly abstract model. One consequence of this is that it is limited in its ability to provide information about the economic efficiency in terms of overall costs or (social) welfare of each policy instrument. However, other studies and theories, notably in environmental economics, have sufficiently clarified the efficiency features of the instruments studied here. Moreover, given the urgency of avoiding extreme climate change, effectiveness in terms of emissions reduction is arguably the most important criterion for judging and selecting instruments of climate policies.

Appendix A Indifference curves

In general, the utility levels of energy sources (4-7) are different from each other. Because of this reason, energy market shares $\mathbf{x}$ converge to a corner solution where one source takes the entire market, as stated by Proposition 2. A value of shares $\tilde{\mathbf{x}}$ that makes utility levels equal, called *indifference* point, exists, but it is not a long run equilibrium, in general. However, the analysis of this value of market shares is informative to understand what makes energy sources more or less attractive, with useful policy implications. For simplicity, we discard cumulation terms, assuming no learning and no peak-oil effect, and do not consider market subsidies. Indifference shares levels are defined as follows:

$$\tilde{x}_c = \frac{1}{4} - \frac{3u_{c0} - u_{s0} - u_{w0} - u_{o0} - 3\tau e_c + \tau e_o}{4\rho} \equiv \frac{1}{4} - \frac{\Delta u_c}{4\rho},$$

$$\tilde{x}_o = \frac{1}{4} - \frac{3u_{o0} - u_{s0} - u_{w0} - u_{c0} - 3\tau e_o + \tau e_c}{4\rho} \equiv \frac{1}{4} - \frac{\Delta u_o}{4\rho},$$

$$\tilde{x}_s = \frac{1}{4} - \frac{3u_{s0} - u_{w0} - u_{o0} - u_{c0} + \tau e_c + \tau e_o}{4\rho} \equiv \frac{1}{4} - \frac{\Delta u_s}{4\rho},$$

$$\tilde{x}_w = \frac{1}{4} + \frac{3u_{w0} - u_{s0} - u_{o0} - u_{c0} + \tau e_c + \tau e_o}{4\rho} \equiv \frac{1}{4} - \frac{\Delta u_w}{4\rho}.$$

Here we have defined the 'effective' profitability gap Δu_a of technology a, for $a =$ *coal*, *gas/oil*, emphsolar, *wind*. Notice that indifference values $\tilde{x}_a$ are only defined if parameters are such that $\frac{1}{4} - \frac{\Delta u_a}{4\rho} \in [0, 1]$. The indifference values defined above suggest a number of considerations. First, the system is symmetric with respect to permutations within the same category (*coal* with *gas/oil* and *solar* with *wind*). Second, there is a condition where the long run value of technology shares is again the equal allocation:

The equations defining indifference values should be read as follows: if a technology a has an intrinsic (not due to market shares) advantage, with a profitability gap Δu_a larger than the others, a lower market share of adoption for that technology a is needed, to make decision makers indifferent between a and the other energy sources. Regarding the increasing returns to adoption factor, the following holds:

Proposition 4 *For a technology a, if $\Delta u_a > 0$, a more intense externality rate ρ leads to a larger indifference share. If $\Delta u_a < 0$ the opposite is true.*

The indifference value of the share of each technology negatively depends on its initial utility value, meaning that for each technology the share of actual adopters is a substitute of the initial profitability value. The share depends positively on the initial profitability of competitor technologies instead (like complement goods), because it has to compensate for that. This is a competition effect. The factor 3 is indeed because each technology faces three competitors.

The first two indifference equations say that carbon taxes are substitutes of renewable shares to make a consumer indifferent. Put differently, in order for renewables to exhaust an equal share the carbon tax must compensate exactly the initial profitability gap. Similarly, the indifference share of *coal* is larger the more *gas/oil* is taxed, and vice-versa. Again, this is due to a substitutability effect in indifference shares.

The substitution effect should be read as follows: assuming that renewables have lower market shares, subsidies and/or taxes are needed to reach the same profitability of fossil fuels (e.g. *grid parity*). But once renewables catch up, the substitution effect is counterproductive, with the unwanted result that clean technologies get lower shares the more they are subsidised, and the more dirty technologies are taxed. At this stage, subsidies and taxes should be replaced by more structural solutions.

Appendix B Dynamic allocation of $R\&D$ subsidies

We have considered a variant of the model, policy scenario III.D2, where tax revenues from the carbon tax are allocated to renewables according to their relative market share, with the ratio $\gamma = \frac{x_s}{x_s+x_w}$ in Eq. (8). This model responds to the idea that $R\&D$ subsidies are more easily allocated to the renewable energy with a larger installed capacity. Figures 19 and 20 report the simulation results for the low and the high level of carbon tax.

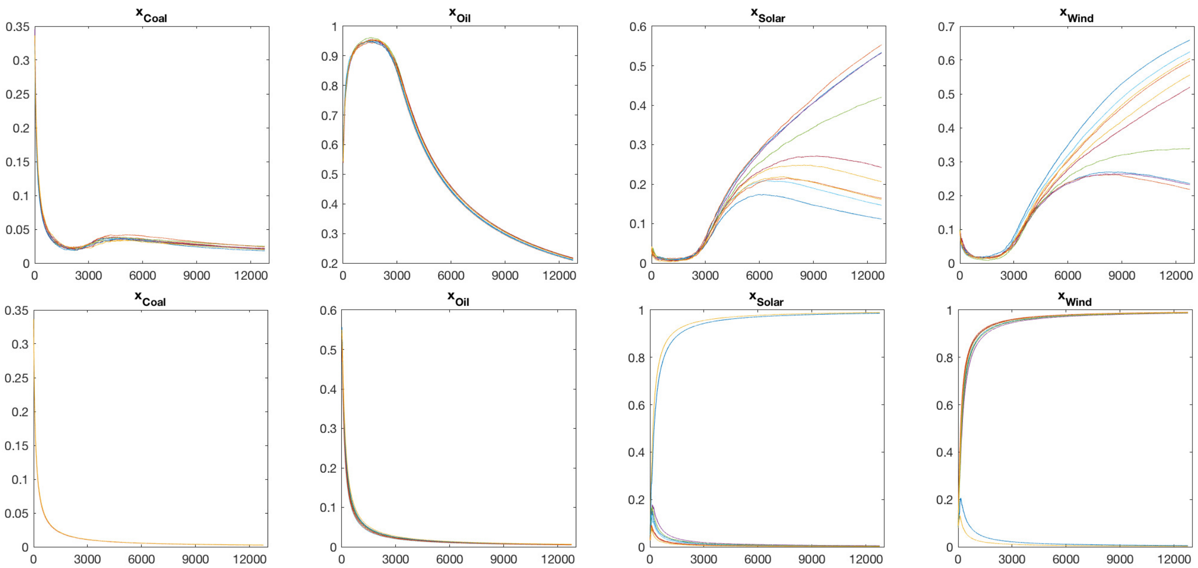

Figure 19: Market shares of the four energy sources (10 simulation runs, in different colours). Scenario (III.D2): dynamic allocation of R&D subsidies for *solar* and *wind* ($\gamma = \frac{x_s}{x_s+x_w}$). Upper panels: carbon tax $\tau = 33\$/tCO_2$. Lower panels: carbon tax $\tau = 125\$/tCO_2$. The horizontal axis reports time in days (time horizon of 35 years). Notice the different scale of the vertical axis in the four panels.

These outcomes look very similar to the fixed allocation $\gamma = 0.5$. Our model is relatively robust to the allocation parameter, in that a dynamic allocation gives the same

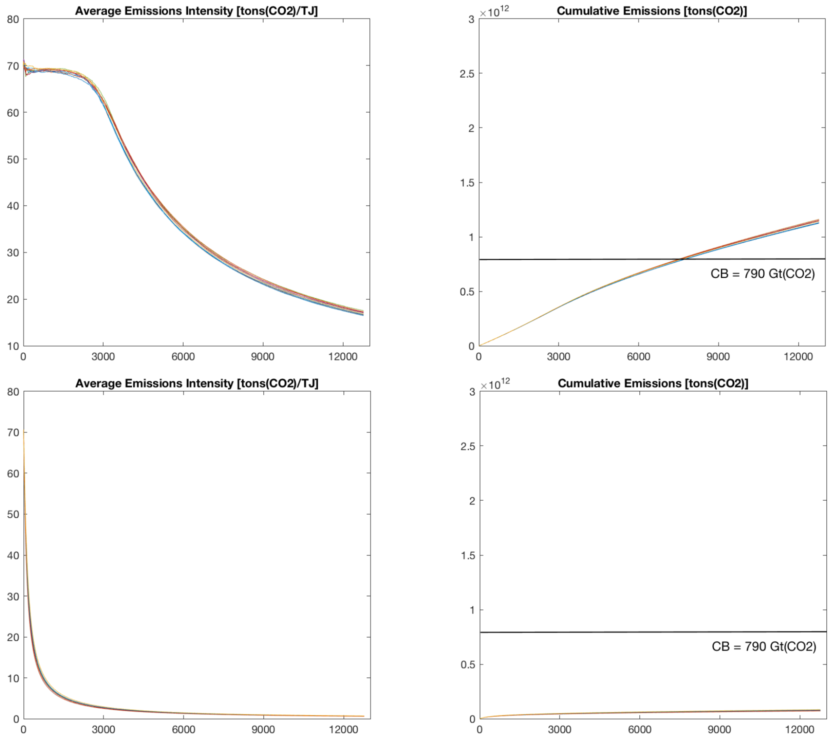

Figure 20: CO_2 emissions (10 simulation runs, in different colours): average emissions intensity of the four energy sources (left) and cumulative emissions over the period 2015 - 2050 (right). Scenario (III.D2): dynamic allocation of R&D subsidies for *solar* and *wind* ($\gamma = \frac{x_s}{x_s + x_w}$). Upper panels: carbon tax $\tau = 33\$/tCO_2$. Lower panels: carbon tax $\tau = 125\$/tCO_2$. The horizontal axis reports time in days (time horizon of 35 years).

results as an even fixed allocation. With a low emission tax, the smaller installed capacity of *solar* is compensated by the relatively stronger learning coefficient, so that approximately the same number of times the two energy sources dominate the market, eventually. With a high emission tax instead, *solar* does not to have the time to catch up most of the times, and *wind* wins in a larger number of simulation runs. What is also interesting is that such outcome occurs both for the fix allocation $\gamma = 0.5$ as for the dynamic allocation. This means that for a policy that re-allocates emission tax revenues to renewable *R&D* outcomes do not depend crucially on the allocation: if the tax level is low, both renewables have approximatively the same chance of dominating the energy market. If it is high, *wind* has a higher chance of becoming the dominant energy source.

Appendix C Sensitivity analysis

We begin our exploration of the model with the rationality parameter β, and limit this sensitivity analysis to the evaluation of market shares of energy sources, as they are the state variable of the model. We set the intensity of increasing returns to $\rho = 2$, and the peak oil parameter to $p = 0.0005$.

Figure 21 contains simulations for $\beta = 0.5$. With such a low value, the system converges to a 'segmented' equilibrium where all four energy sources are represented by a sizeable market share, although this is different from the equal allocation of the case $\beta = 0$. We also notice a large variability of time series of different simulation runs.

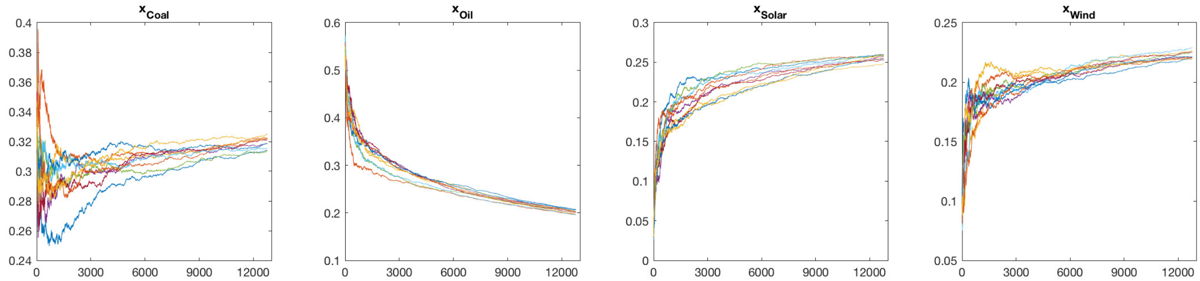

Figure 21: Market shares of the four energy sources (10 simulation runs, in different colours). Parameters: $\beta = 0.5$, $\rho = 2$, $p = 0.0005$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

With $\beta = 1.5$ (Figure 22) the outcome of the baseline setting of Scenario I (No Policy) emerges: *coal* prevails clearly, and peak pattern for *oil/gas* is present in the early 2000 periods of the simulations. However, the final attractor of the dynamic system seems to be an allocation vector different from the corner solution where only one energy source is adopted (*coal*). This is the result of a still relatively low rationality parameter β, which allow sub-optimal sources to be adopted. Notice also the relatively larger variability of market shares time series, which indicates a setting that is in between the internal equilibrium characterising a low β and the corner equilibrium of a large β.

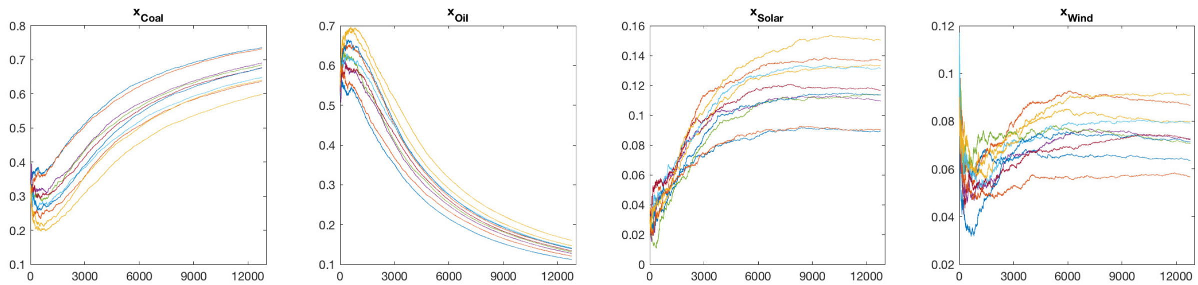

Figure 22: Market shares of the four energy sources (10 simulation runs, in different colours). Parameters $\beta = 1.5$, $\rho = 2$, $p = 0.0005$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

The simulations of Figure 23, with $\beta = 3$, present already the patterns of Scenario I, which has $\beta = 4$: market shares converge to the corner solution where *coal* prevails, while in the transitory dynamics we see a peak pattern for *oil/gas* and a 'delayed' peak pattern for *solar* first, and then *wind*. Moreover, the variability of simulated time series is lower than with $\beta = 1.5$ which indicates that around $\beta = 3$ the systems converges relatively

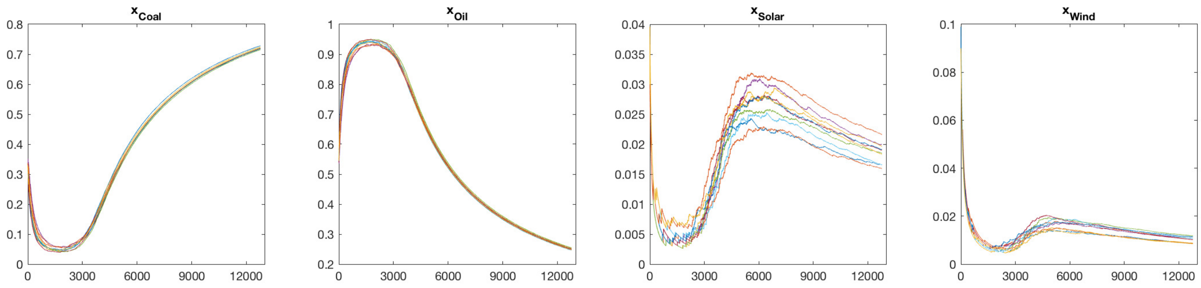

Figure 23: Market shares of the four energy sources (10 simulation runs, in different colours). Parameters: $\beta = 3$, $\rho = 2$, $p = 0.0005$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

quickly and without much variation to the corner solution of *coal* prevailing. Higher values of β do not alter the qualitative behaviour of outcomes, apart from a further reduction of variability. With $\beta = 10$ all simulations look almost the same (Figure 24).

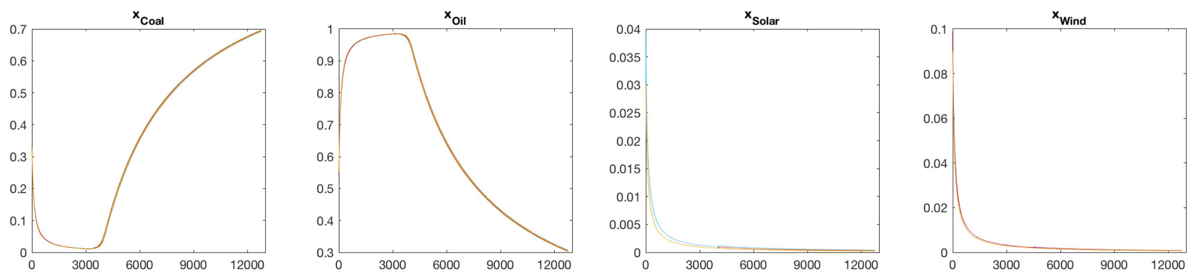

Figure 24: Market shares of the four energy sources (10 simulation runs, in different colours). Parameters: $\beta = 10$, $\rho = 2$, $p = 0.0005$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

We now turn to the parameter ρ, which express the intensity of positive feedback in sequential decision stemming from all mechanisms of increasing returns to adoption, like technological positive externalities, infrastructure, learning by doing, social influence, etc.

When the intensity ρ is very low, as in Figure 25 with $\rho = 0.1$, the energy source that is more diffused initially, *oil/gas* starts declining immediately, due to the peak-oil effect which is now relatively important already. As a result, the three other energy sources gain in market share. It is *coal* that becomes the most widely used source in less than 700 time steps (about two years), with *solar* and to some extent also *wind* also growing. We have observed with longer time horizons that *coal* starts to decline after 20000 time steps, with renewables slowly conquering the market. But this time corresponds to more than 50 years, for which our calibration would not be meaningful. Peak oil and Learning are the most important dynamic terms in this setting, which explain the decline of *oil/gas*, the temporary success of *coal*, and the steady growth of renewables.

For $\rho = 1$ simulations show already the pattern of scenario (I), although they present

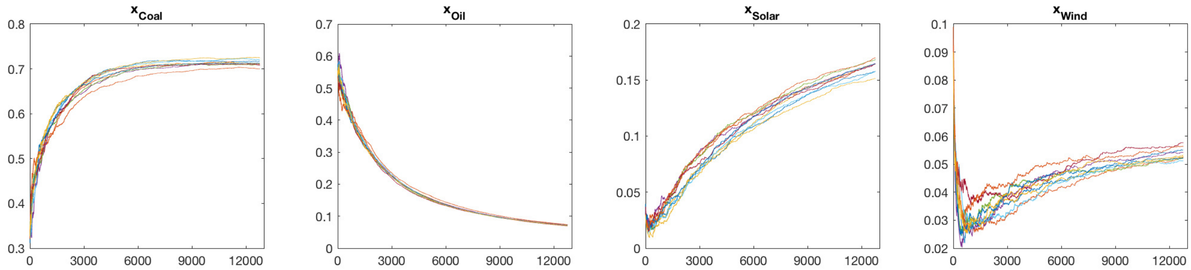

Figure 25: Market shares of the four energy sources (10 simulation runs, in different colours). Parameters: $\rho = 0.1$, $\beta = 10$, $p = 0.0005$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

a much higher variability of different runs (Figure 26).

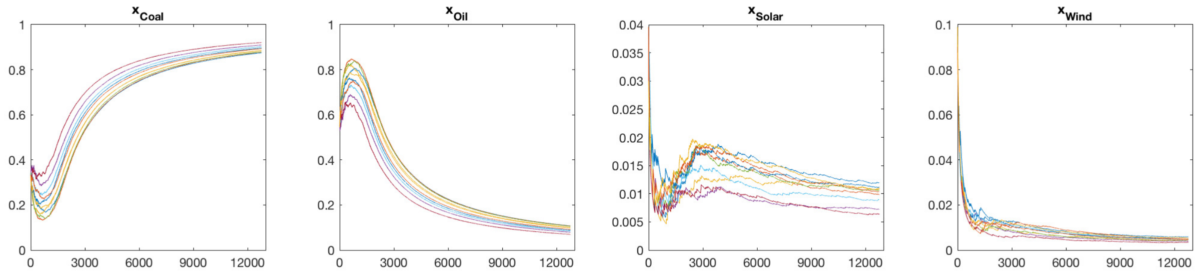

Figure 26: Market shares of the four energy sources (10 simulation runs, in different colours). Parameters: $\rho = 1$, $\beta = 4$, $p = 0.0005$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

A value $\rho = 2$ is what we use in our main simulation study. With a stronger intensity of positive feedback, as $\rho = 3$, we obtain the results of Figures 27. The main effect of a

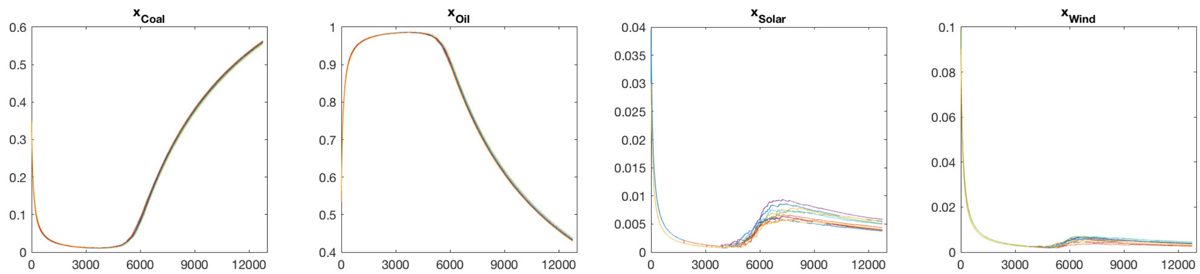

Figure 27: Market shares of the four energy sources (10 simulation runs, in different colours). Parameters: $\rho = 3$, $\beta = 4$, $p = 0.0005$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

more intense positive feedback is the extension of the peak oil, intended as a longer time span during which *oil/gas* market share stays above 90%: from about 4000 days (or 11 years) for $\rho = 2$ (Figure 3), to about 5500 days (or 15 years). With such extended period of *oil/gas* dominance, the resurrection of the other energy source is delayed accordingly,

Table 2: Scaling pattern of peak oil window and time of carbon budget exhaustion (I)

intensity of feedback	peak-oil width (days)	time-2^oC (days)
$\rho = 2$	4000	5600
$\rho = 3$	5500	5740
$\rho = 4$	8000	5740
$\rho = 5$	5500	5750
$\rho = 6$	13000	5750
$\rho = 10$	> 13000	5750

Scaling pattern of peak oil window and time when total emissions exhaust the carbon budget, for an increasing intensity of increasing returns to adoption ρ.

with the peak in the renewable market shares occurring after about 7000 days (19 years). However, renewables shares remain always below 1%. A second effect of a larger ρ is the reduced variability of different simulation runs.

For larger values of ρ the qualitative dynamics of the model does not change. What is interesting it is the scaling pattern of the width of the peak oil and the time when the total cumulated stock of CO_2 exhausts the carbon budget of 790 $Gt(CO_2)$. We report the outcomes in table 2. While the time windows of *oil/gas* dominance increases almost linearly (apart from the initial step) with ρ (adding about 2500 days, or 7 years) every unitary increase of ρ, the time of the stock exhausting the carbon budget converges to the value 5750 days, which corresponds to slightly less than 16 years. All this indicates that while ρ is a crucial parameter for the transitory competition dynamics of the sequential decision system in this model, the model is very robust in terms of cumulative CO_2 emissions and in particular the time when the the carbon budget runs up: no matters how intense the increasing returns on adoption are, the carbon budget is exhausted at a time which does not go beyond 16 years, despite peak oil.

This result is robust also to changes in the rationality parameter β. With $\beta = 10$, the values in the table 2 are barely affected at all. The final conclusion is that while β reduces the variability of simulated choices only, ρ does affect the competition dynamics of energy sources, but only in terms of the substitution between *coal* and *oil/gas*. The resulting aggregated outcome expressed by the total emitted stock is practically unaffected by ρ.

This finding has two implications. The first is that to delay or avoid total emission to exhaust the carbon budget we need a transition to renewables, with these obtaining a lasting share of the energy market. The second is that messages from our model regarding the feature of such transition, and the condition that favour them are quite robust.

Finally, we study the sensitivity of our model to changes in the parameter p, that sets the weight of the peak oil term in the utility of *oil/gas* in Eq. (5). For the other parameters we set $\beta = 4$ and $\rho = 2$, as in the main policy simulation scenarios of Section 4. Figures 28, 29 and 30 report the simulated time series of competing market shares of energy sources for the values $p = 0.0001$, $p = 0.001$ and $p = 0.005$, respectively. To these,

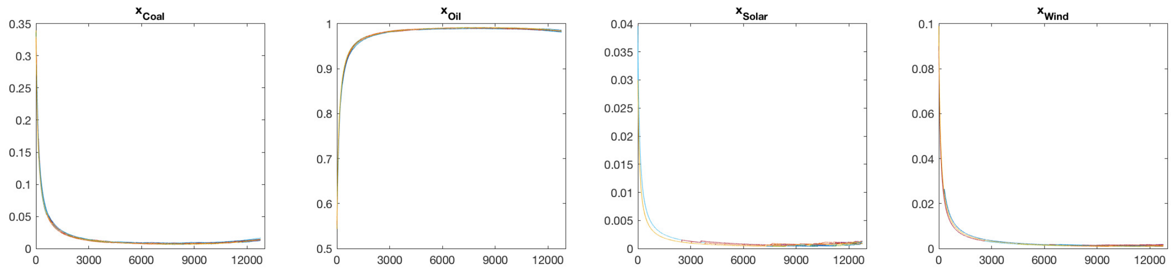

Figure 28: Simulated time series of the four energy shares (10 runs, in different colours). Parameters: $p = 0.0001$, $\beta = 4$, $\rho = 2$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

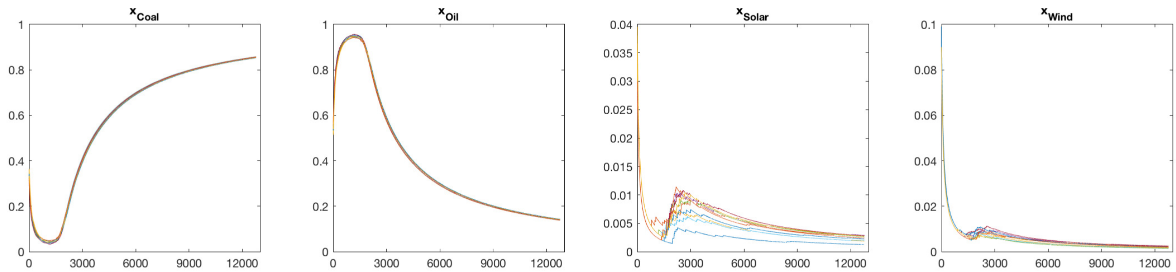

Figure 29: Simulated time series of the four energy shares (10 runs, in different colours). Parameters: $p = 0.001$, $\beta = 4$, $\rho = 2$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

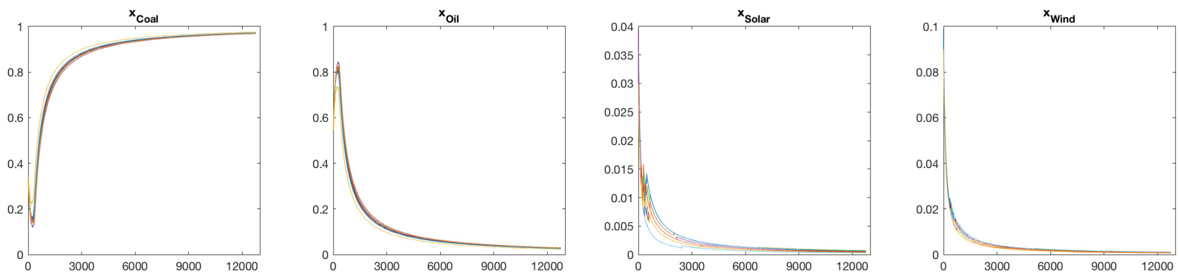

Figure 30: Simulated time series of the four energy shares (10 runs, in different colours). Parameters: $p = 0.005$, $\beta = 4$, $\rho = 2$. The horizontal axis is time (days units, 35 years). Notice the different scale of the vertical axis in the four panels.

the case $p = 0.0005$ of Figure 4 can be added, which represents the baseline Scenario (I) of Section 4. We observe the following: the parameter p is responsible for the time width of the peak oil. When we simulate the model with $p = 0$ we obtain no peak oil

Table 3: Scaling pattern of peak oil window and time of carbon budget exhaustion (II)

peak oil parameter p	peak oil width (days)	time of carbon budget exhausted (days)
$p = 0$	∞	5750
$p = 0.0001$	> 13000	5750
$p = 0.0005$	3000	5600
$p = 0.001$	1500	5250
$p = 0.005$	500	4650
$p = 0.01$	~ 100	4550
$p = 0.05$	~ 0	4470
$p = 0.1$	~ 0	4460

Scaling pattern of peak oil window and time when the carbon budget is exhausted, for an increasing peak oil parameter p.

at all, as expected. *oil/gas* market share grows and converges to 100%, while the other energy sources disappear from the energy market. With a tiny peak-oil factor, there is a temporary complete dominance of *oil/gas*, which exhausts almost 100% of the market, and just starts declining at the end of our simulation time horizon of 12775 days, or 35 years (Figure 28) As p increases (the case $p = 0.0005$ in Figure 4 and $p = 0.001$ in Figure 29), the duration of the time period where *oil/gas* is dominant shrinks considerably. For $p = 0.005$ there is a kind of immediate and sharp peak-oil effect, which practically corresponds to an immediate drop in *gas/oil* shares. All this translates into a delayed peak for shares of renewables that moves back in time correspondingly, as well as the time when *coal* shares surge to seize the entire energy market.

Peak oil and an earlier *coal* take-off determine an earlier time when total cumulative CO_2 emissions exhausting the carbon budget of 790 $Gt(CO_2)$. In table 3 we have recorded the time duration of the peak oil (expressed as the time interval where *oil/gas* market shares stay at 10% or less from the peak value) and the time of carbon budget exhausted by total emissions, for different values of the parameter p. From this pattern it emerges that while the peak oil width shrinks with an increasing value of p the time when the carbon budget is exhausted scales down at a decreasing speed. For instance, doubling p from $p = 0.0005$ to $p = 0.001$ takes the time of achievement of the carbon budget from $t \simeq 5600$ to $t \simeq 5250$, while doubling from $p = 0.005$ to $p = 0.01$ takes this time from $t \simeq 4650$ to $t \simeq 4550$, a decrease of only 100 days.

To conclude, similarly to the increasing returns parameter ρ also p has a heavy impact on the transitory competition dynamics of energy sources, but an increasingly limited impact on the time when the carbon budget is exhausted. Once again, even with learning for renewable sources, the carbon budget can not be avoided unless a climate policy is set in action, and the results obtained in this sense are robust with respect to changes in the behavioural parameters like β and ρ as well as to change sin the peak oil parameter p.

Acknowledgments
We thank Ivan Savin for useful comments on the manuscript. The paper has benefited from presentations at Fondazione ENI Enrico Mattei (Milan, Italy) and the Institute for New Economic Thinking (Oxford, UK). Jeroen van den Bergh received support through an ERC Advanced Grant from the European Research Council (ERC) under the European Union's Horizon 2020 Research and Innovation Programme [grant agreement n^o 741087].

References

Arthur, B. (1989): "Competing technologies, increasing returns, and lock-in by historical events," *Economic Journal*, 99, 116–131.

Arthur, W., Y. Ermoliev, and Y. Kaniovski (1987): "Path-dependent processes and the emergence of macrostructure," *European Journal of Operation Research*, 30, 294–303.

Baranzini, A., J. van den Bergh, S. Carattini, R. Howard, E. Padilla, and J. Roca (2017): "Carbon pricing in climate policy: Seven reasons, complementary instruments, and political-economy considerations," *Wiley Interdisciplinary Reviews: Climate Change*, 8, e462.

Brock, W. and S. Durlauf (2001): "Discrete choice with social interactions," *Review of Economic Studies*, 68, 235–260.

Brock, W. and C. Hommes (1997): "A Rational Route to Randomness," *Econometrica*, 65, 1059–1095.

Chapman, I. (2014): "The end of Peak Oil? Why this topic is still relevant despite recent denials," *Energy Policy*, 64, 93–101.

Coady, D., I. W. Parry, L. Sears, and B. Shang (2015): *How large are global energy subsidies?*, 15-105, International Monetary Fund.

Dasgupta, P. S. and G. M. Heal (1979): *Economic theory and exhaustible resources*, Cambridge University Press.

Farmer, J. D. and J. Trancik (2007): "Dynamics of technological development in the energy sector," *London Accord Final Publication.*

Holland, S. P. (2008): "Modeling peak oil," *The Energy Journal*, 61–79.

Holland, S. P. et al. (2013): "The economics of peak oil," *Encyclopedia of Energy, Natural Resource, and Environmental Economics*, 1, 146–150.

Hommes, C. (2013): *Behavioral Rationality and Heterogeneous Expectations in Complex Economic Systems*, Cambridge, England: Cambridge University Press.

Hommes, C. H. (2006): "Heterogeneous Agent Models in Economics and Finance," in *Agent-based Computational Economics*, ed. by L. Tesfatsion and K. L. Judd, Amsterdam: North-Holland, vol. 2 of *Handbook of Computational Economics*, chap. 23, 1109–1186.

Katz, M. L. and C. Shapiro (1985): "Network externalities, competition and compatibility," *American Economic Review*, 75, 424–440.

King, L. C. and J. C. van den Bergh (2018): "Implications of net energy-return-on-investment for a low-carbon energy transition," *Nature Energy*, 1.

McFadden, D. L. (1981): "Structural discrete probability models derived from theories of choice," in *Structural analysis of discrete data and econometric applications*, ed. by C. Manski and D. L. McFadden, Cambridge, US: MIT Press.

OECD and IEA (2017): "Perspectives for the Energy Transition - Investment needs for a Low-Carbon Energy System," Tech. rep., OECD/IEA and IRENA.

Peters, G. P. (2018): "Beyond carbon budgets," *Nature Geoscience*, 11, 378.

Rogelj, J., M. Schaeffer, P. Friedlingstein, N. P. Gillett, D. P. Van Vuuren, K. Riahi, M. Allen, and R. Knutti (2016): "Differences between carbon budget estimates unravelled," *Nature Climate Change*, 6, 245.

Rubin, E. S., I. M. Azevedo, P. Jaramillo, and S. Yeh (2015): "A review of learning rates for electricity supply technologies," *Energy Policy*, 86, 198–218.

Safarzyńska, K., K. Frenken, and J. C. van den Bergh (2012): "Evolutionary theorizing and modeling of sustainability transitions," *Research Policy*, 41, 1011–1024.

Stern, N. and J. Stiglitz (2017): "Report of the high-level commission on carbon prices," Tech. rep., World Bank Group, Washington D.C.

van den Bergh, J. C. and W. J. Botzen (2014): "A lower bound to the social cost of CO_2 emissions," *Nature climate change*, 4, 253.

Zeppini, P. (2015): "A discrete choice model of transitions to sustainable technologies," *Journal of Economic Behavior and Organization*, 112, 187–203.

Zeppini, P. and J. C. J. M. van den Bergh (2011): "Competing Recombinant Technologies for Environmental Innovation: Extending Arthur's Model of Lock-In," *Industry & Innovation*, 18, 317–334.